

Predicting Property Crime Risk: an Application of Risk Terrain Modeling in Vancouver, Canada

Martin A. Andresen¹ · Tarah Hodgkinson¹

Published online: 23 May 2018

© Springer Science+Business Media B.V., part of Springer Nature 2018

Abstract Research on the spatial dimension of crime has developed significantly over the past few decades. An important aspect of this research is the visualization of this dimension and its underlying risk across space. However, most methods of such visualization, and subsequent analyses, only consider crime data or, perhaps, a population at risk in a crime rate. Risk terrain modeling (RTM) provides an alternative to such methods and can incorporate the entire environmental backcloth, data permitting. To date, the RTM literature has dominantly focused on violent crime in the United States. In this paper, we apply RTM to property crime victimization (residential burglary) in Vancouver, Canada. We are able to show that not only does RTM have applicability in a Canadian context but provides insight into nonviolent victimization.

Keywords Risk terrain modeling · Residential burglary · Canada

Introduction

Burglaries¹ have been declining in Canada since the mid-1990s,² with a total of 157,869 incidents and a rate of 435 per 100,000 persons in 2016.³ Although the number of burglaries

¹Break and enter is the legal term for burglary in Canada. However, to remain consistent with the current literature on burglary, we use the term burglary for the purposes of this study.

²Despite a slight increase in 2015 of 4%, the number of break and enters have declined more than 40% since 2005. <http://www.statcan.gc.ca/pub/85-002-x/2016001/article/14642/tbl/tbl05-eng.htm>

³<http://dc1.chass.utoronto.ca/cansimdim/>

✉ Martin A. Andresen
andresen@sfu.ca

Tarah Hodgkinson
thodgkin@sfu.ca

¹ School of Criminology and Institute for Canadian Urban Research Studies, Simon Fraser University, Burnaby, BC, Canada

has declined, these incidents still account for a large portion of property crime in Canada and affect victims both financially and psychologically (Waller 2010). The ability to forecast burglary locations could contribute to both prevention and appropriate allocation of police resources. However, current mapping methodologies typically only use previous burglaries to predict future incidents (Caplan et al. 2013). Though there is research that speaks to the likelihood of repeat victimization (Farrell and Pease 1993), this method is more retrospective than predictive (Caplan et al. 2011) and only addresses one aspect of risk for this type of crime. This is problematic because it assumes ecological stability and ignores other potential correlates of crime (Andresen 2014). To date, few studies have attempted to move past retrospective methodologies and examine other spatial cues in predicting the risk of burglaries (for an exception, see Moreto et al. 2014). The current study expands upon this research by examining the reliability of these spatial cues in the Canadian context and addressing other potential risk factors within the environmental backcloth.

Related Research

Property crimes, such as burglary, have been studied in numerous contexts and from several methodological approaches, including ethnographic interviews (Waller 1979; Cromwell et al. 1991; Armitage and Joyce 2016) and hotspot analyses (Townshley et al. 2003; Johnson and Bowers 2004). Research into individual motivating factors for committing this type of property crime has been illuminating and contributed to determining the risk factors that emerge spatially. For instance, offenders are often seeking means to obtain drugs and alcohol for related addiction issues (Cromwell et al. 1991; Mawby 2001; Armitage and Joyce 2016). Thus, proximity to locations with known drug markets or where stolen goods can be converted into cash may increase the risk in a particular area (Moreto et al. 2014).

Additionally, spatial research on burglaries has found that certain homes are repeatedly victimized (Farrell et al. 1995; Farrell and Pease 1993). This is, in part, is because the offender learns how to enter the home (Farrell and Pease 1993), as the targets are known and access is easier. Furthermore, the victim usually replaces the stolen items within a short time frame and, thus, new goods are available to steal. Recent research has demonstrated that once a house has been burglarized, surrounding homes are at an increased risk of similar victimization within a short time frame. This is identified as a near-repeat phenomenon and, again, is the result of information gained by the offender in the initial burglary (Townshley et al. 2003; Johnson et al. 2007).

In recent years there has been a shift from analyzing incidents of burglaries to analyzing risk factors (Johnson et al. 2009; Moreto et al. 2014). This is an important change methodologically, because many studies have used mapping techniques such as kernel density and hot-spot analyses that apply a continuous surface to discrete crime events. These techniques are problematic because they may assign positive values to places that do not experience crime incidents. This is important because decades of research have demonstrated that some places do not experience crime, a fact that has been identified in numerous research studies around the world (Andresen et al. 2017; Sherman et al. 1989; Weisburd 2015; Weisburd and Amram 2014). Risk, however, is a continuous phenomenon and is therefore a more appropriate independent variable than the use of previous incidents of crime.

Risk terrain modeling allows the researcher to examine the risk heterogeneity of an area, coupled with event-specific evaluations of crime, to create a more comprehensive appreciation of how crime manifests in particular locations (Weisburd et al. 2006; Kennedy et al. 2011;

Caplan et al. 2013). Thus, risk terrain modeling (RTM) is largely influenced by environmental criminology, specifically the environmental backcloth (Brantingham and Brantingham 1981). This backcloth (Brantingham and Brantingham 1993) is a dynamic setting consisting of both physical elements, such as buildings or transportation nodes, and how these elements influence the landscape and how the individual navigates that landscape in their routine activities.

Environmental criminologists examine the opportunities that emerge as an assumed rational offender moves through space making decisions about whether to take advantage of these opportunities. The rational choice theory (Clarke and Cornish 1985) posits that offenders weigh the risks and rewards associated with committing a crime and act only when the reward outweighs the risk of apprehension. The offenders determine these risks and rewards by taking cues from the surrounding environment. In accordance with the routine activities perspective, offenders move through space independent of target seeking. Rather, they become exposed to opportunities to offend while carrying out their day-to-day routines (Cohen and Felson 1979). This environmental backcloth includes both crime generators (locations that create opportunities for crime) and crime attractors (locations that attract offenders because of the behaviors that occur there) and can lead to crime concentrating into certain areas or hotspots (Brantingham and Brantingham 1995).

Research in environmental criminology has demonstrated that crime is not evenly distributed and tends to concentrate spatially (Weisburd 2015). Furthermore, certain hotspots tend to remain hotspots over time (Weisburd et al. 2004; Groff et al. 2010; Curman et al. 2015). This is likely a result of environmental risk factors at these locations. For example, a cumulation of certain criminogenic risk factors should increase the vulnerability of a location compared with other locations without these risk factors (Kennedy et al. 2016). Furthermore, though less frequently discussed in the environmental criminological literature, this could also be a product of the stable nature of social ecological factors that contribute to social disorganization (Shaw and McKay 1942; Sampson and Groves 1989). Considering both environmental factors and social ecological variables, to identify and address variables in the environmental backcloth that contribute to an increased risk of victimization, a place-based model that operationalizes these risks would address some of the current limitations in typical mapping methodologies (Caplan et al. 2011).

Opportunities for crime are difficult to measure and operationalize. Alternatively, certain factors that contribute to the likelihood of a location being targeted can be operationalized as risk (Caplan et al. 2011). Thus, RTM allows researchers to determine the correlates of the environmental backcloth that contribute to particular types of crime (Caplan et al. 2011).⁴ These correlates create the risk surface, a continuous measure that predicts the likelihood of crime occurring in certain areas (Caplan et al. 2011). This is appropriate for geospatial testing, such as hotspot and kernel-density analyses that also apply a continuous surface in their analysis (Caplan et al. 2011).

Caplan et al. (2011) identified risk factors for most crime types, such as arson, all types of assault, homicide, robbery and shootings, and theft and burglaries in their risk terrain compendium. RTM has typically been used to predict violent crimes. Tests of the model with property crime are less common, however, and more research on the application of the model is needed for property crimes. Moreto et al. (2014) applied RTM to burglaries, and their study is a springboard for the study we report here.

⁴ Moreto et al. (2014) takes an important step and operationalizes the environmental backcloth. They argue that, often, this backcloth can be broken down into three main factors: physical, person–environment, and demographic (socioeconomic and cultural).

Moreto et al. (2014) examined the role of several risk variables, including land use (particularly residential land use), at-risk housing, pawn shops, offender residences, drug markets, and public transportation nodes. Residential land use is more likely to be at risk of burglary, as there are more targets present (Groff and La Vigne 2001). At-risk housing, as defined in their study, suffers from both poor guardianship and related drug issues, known risk factors associated with burglary victimization (Moreto et al. 2014; Reynald 2011; Cromwell et al. 1991). Pawn shops are an appropriate risk factor, as they allow the offender to quickly transfer stolen goods into cash (Wright and Decker 1994). Proximity to offender residences should increase the risk of victimization, as these locations are within offenders' awareness space, where they have the ability to monitor routine activities (Wright and Decker 1994; Forrester et al. 1988; Bernasco and Nieuwbeerta 2005; Bernasco 2006).⁵ Proximity to drug markets allows for quick purchase of drugs (Cromwell et al. 1991; Mawby 2001).⁶ Finally, nearby transportation nodes allow for quick escape (Clare et al. 2009). Moreto et al. (2014) calculated the risk of near-repeat events and found that near-repeat events contributed to the overall risk model. However, because of the nature of open crime data⁷ in the study reported here, this risk factor could not be included.

This study incorporates available risk factors from Moreto et al.'s (2014) study and additional risk factors. We include land-use data (expanded with type of residential dwellings and mixed land use), pawn shops, transportation nodes, and at-risk housing. We operationalize at-risk housing as being not-for-profit housing, and we separate pawn shops into pawn brokers and second-hand dealers as they are defined differently in the Canadian context. The other risk factors in this study were not available to the researchers. In addition to these risk factors, we include a number of social disorganization and guardianship variables, as these are known correlates of crime in general. These are important for situating the research in a larger literature that consistently finds correlation between ecological factors associated with social disorganization and increased levels of crime (Shaw and McKay 1942). We include variables such as ethnic heterogeneity, population turnover, socioeconomic status, percentage of young men (the typical offending population), and education levels. We include additional variables from the crime prevention literature that contribute to the risk of victimization, including the percentage of rental units and percentage of locations requiring major repairs or undergoing construction (Cozens et al. 2005; Cozens and Love 2015). These locations may experience increased risk, as guardianship behaviors may be negligible, and upkeep of image and maintenance may be poor (Reynald 2011; Wilson and Kelling 1982). These variables will extend the understanding of the nature of risk for burglaries in Canada. Further reasoning for inclusion of these variables in the risk surface is discussed below.

Data and Methods

Vancouver has a population of >600,000 people and is one of Canada's ten largest cities. It is located on the west coast and is geographically quite small despite its dense population. The

⁵ This data was not available for the current study, as analysis relied on open-data sources.

⁶ In Vancouver, only one drug market has been openly identified. This exists in the downtown east side. This area suffers from a number of social disorder issues and income instability that has caused it to be labeled "the poorest urban postal code in Canada." Thus, for the current study, this location was not directly included as a variable but it is discussed in the results.

⁷ Specifically, that open crime data available for Vancouver is not geocoded to an address but to the 100-block level (street block).

burglary rate is 467 per 100,000 population, and the number of burglaries in 2016 was 2946, down from 5466 in 2005. . All areas of the city, including industrial areas, are included, despite burglary being unlikely in these locations; however, our zoning variable controls for this concern (Moreto et al. 2014).

Crime, Spatial Units of Analysis, and Risk/Census Variables

This study used residential burglary crime incident data for Vancouver obtained from the Vancouver Open Data Catalog.⁸ Variables in these data include location (100-block), date, time, location, and year. Residential burglary data are available from 2003 to 2017, but we used 2011 and 2012 data because of the availability of the 2011 Census of Population data, which we used to build the risk terrain surface to test against data from the following year. All crime data are provided with geographic locations, including latitude and longitude coordinates. These coordinates are not specific to an address but to the center of the respective street segment, or 100-block. However, as we used spatial units of analysis larger than the street segment, there are no concerns for data accuracy.

Spatial units of analysis are dissemination areas (DAs) defined by Statistics Canada for the 2011 Census of Population. Vancouver has an approximate area of 115 km² and 992 DAs, which are smaller than the more traditionally used census tracts. DAs are equivalent in size to the census block group used in the US census of ~400–700 persons contained within one or two city blocks. We use DAs as the spatial unit of analysis because most of our risk factors are measured at the DA level—point-level data were aggregated to their respective DAs. This breaks from much of the RTM literature that uses relatively small grids (150 m²) and point-level risk factors; however, using DAs allows us to incorporate point-level risk factors as well as many more ecological variables. Moreover, DAs are sufficiently small (350 m², on average), so the “spatial cost” of incorporating more theoretically informed variables is relatively low. However, we acknowledge that these variables are best gathered at the micro level as well (Braga and Clarke 2014). We consider this to be correct use of the RTM method because we are still identifying risk factors and generating a risk surface. Regardless, this is a new and instructive contribution to the RTM literature. As such, in this research, we contribute to the methodological aspect of RTM in that risk factors for crime may be identified at a number of different spatial scales.

To identify risk factors for residential burglary, we consider research within the RTM literature (Moreto et al. 2014) as well as social disorganization (Lowenkamp et al. 2003; Sampson and Groves 1989; Shaw et al. 1929; Shaw and McKay 1931, 1942) and the routine activity theory (Cohen and Felson 1979; Felson and Eckert 2016; Kennedy and Forde 1990). Moreto et al. (2014) identify land use, at-risk housing (defined at housing with drug activity and low guardianship), pawn shops, burglar residences, drug markets, and public transportation nodes (light-rail rapid transit stations)⁹ as risk factors. Data available for the current study were land use (mixed land use, multifamily residential, two-family residential, single-family residential) measured in hectares, not-for-profit housing, pawn shops, second-hand dealers, and major public transportation nodes (light-rail rapid transit stations).

⁸ <http://data.vancouver.ca/datacatalogue/crime-data.htm>

⁹ The light-rail rapid transit stations (Skytrain stations) represent public transportation nodes in our analyses. These stations are commonly setting for bus loops (many bus lines begin and terminate at these stations).

The importance of land use has a long history in the criminological literature (Groff and La Vigne 2001; Kinney et al. 2008). We did not have at-risk housing data (Moreto et al. 2014), but to capture housing that may have lower guardianship, we include not-for-profit housing. Not-for-profit housing often experiences increased levels of risk because of lack of security and the transitional nature of residents (Davies 2006). Wright and Decker (1994) identified the proximity of pawn shops for quick disposal of stolen goods; we also include second-hand dealers because they may also be instructive on that front. Public transportation nodes are included for ease of burglar access/exit and measuring potential awareness spaces (Clare et al. 2009).

Sampson and Groves (1989) outlined the causal model for the social disorganization theory. They showed that sparse local friendship networks, unsupervised teenage peer groups, and low organizational participation were mediating factors between variables of social disorganization and increases in crime. However, few studies have been able to include such variables, particularly for a city-wide neighborhood-level analysis [see Lowenkamp et al. (2003) for a rare replication of Sampson and Groves (1989) original work]. Consequently, census variables measured at the neighborhood level (census tracts or, in this study, DAs) are used to capture data on low economic status, ethnic heterogeneity, residential mobility, family disruption, and urbanization.

Economic status is measured considering postsecondary education, unemployment rate, median income, and government assistance payments (welfare, unemployment benefits, childcare benefits, etc.). Ethnic heterogeneity is measured with recent immigration and visible minorities. Literature regarding the social disorganization theory often expects ethnic heterogeneity to be positively associated with crime because of increased difficulties for immigrants forming organizational participation due to language barriers, for example. However, much of the recent research on immigration and crime has found either a negative or statistically insignificant relationship (MacDonald et al. 2013; Stansfield et al. 2013). As such, recent immigration is expected to have a negative relationship with residential burglary. Residential mobility is measured using the percentage of the population that moved in the previous year and percentage of rented households. No variables were available for family disruption, commonly defined by the divorce rate in the spatial criminology literature. As Vancouver is considered an urban center, no urbanization variable was included. To capture motivated offenders, young men (15–24 years) were included as they make up the largest percentage of the offending population and should potentially contribute to risk (Hirschi and Gottfredson 1983). Suitable targets are measured using the number of dwellings, as greater density could indicate high-rise buildings that often offer more security by controlling access (Crowe 2000), and median housing value, to potentially capture higher-valued opportunities (Andresen 2011a, 2011b). Furthermore, the rational choice theory would predict that houses that offer more rewards (more expensive) will be more desirable to motivated offenders, although research findings on this link are inconclusive and require further investigation (Armitage 2013). We used median instead of average housing value because of the skewed nature of these data. Descriptive statistics for dependent (residential burglary) and independent (risk factors) variables are shown in Table 1.

Risk Terrain Modeling Methods

As noted above, RTM considers the risk of crime occurring at a place and considers previous criminal events (hotspot mapping, e.g.) and social, demographic, economic, and physical characteristics of the environment (Kennedy et al. 2011). The general technical approach to RTM is straightforward: identify risk factors (listed above), operationalize to a common geography for all risk factors (DAs, e.g.), and assign a value for each risk factor that identifies

Table 1 Descriptive statistics; dependent and independent variables

Variables	Minimum	Maximum	Mean	SD
Burglaries, 2011	0	20	3.26	2.66
Burglaries, 2012	0	29	3.34	2.70
Burglary rate, 2011	0	125.00	15.29	14.61
Burglary rate, 2012	0	100.00	15.04	13.18
Number of dwellings	0	2290	266.65	180.69
Young men, %	0	24.75	6.78	4.82
Recent immigrants, %	0	39.53	6.38	6.36
Visible minorities, %	0	101.10	51.47	25.88
Mobility, 1 year, %	0	57.61	16.41	10.56
Postsecondary education, %	0	97.96	71.68	15.13
Unemployment rate	0	64.70	6.02	6.32
Public transportation, %	0	68.18	29.27	12.13
Major repairs, %	0	54.24	6.03	8.40
Rentals, %	0	102.33	45.38	25.93
Median dwelling value, 000s \$	224.83	4004.17	887.98	520.22
Median income, 000s \$	0.94	74.55	29.14	10.38
Government assistance, %	0	79.20	10.65	7.66
Skytrain stations	0	2.00	0.02	0.16
Mixed land use, %	0	104.44	1.72	6.03
Multifamily dwellings, %	0	7.49	0.80	1.39
Two-family dwellings, %	0	16.59	0.77	1.85
Single-family dwellings, %	0	407.61	6.72	15.13
Not-for-profit housing	0	7	0.17	0.67
Pawnbrokers	0	2	0.01	0.12
Second-hand dealers	0	14	0.23	0.86

n = 992

SD standard deviation, *000s \$* amount in thousand dollars (CAD)

presence, absence, intensity, or some other metric for all units of analysis. Once all risk factors are operationalized, separate coverage maps (shapefiles or rasters) are created for each factor and combined to generate a composite map, or risk: the simplest case is adding the presence/absence for each risk factor in each geography [see Moreto et al. (2014), e.g.]. Assigning risk values to the various geographies has become more sophisticated with the development of RTM software: the Risk Terrain Modeling Diagnostics Utility (RTMDx) (Barnum et al. 2017; Caplan and Kennedy 2013; Kennedy et al. 2016). However, as our data are mostly continuous variables, we employed an intermediate level of sophistication when generating our risk terrain surface.

Due to the distribution of residential burglary events, negative binomial regressions (count data models) were estimated using robust standard errors (SE) to identify statistical significance for risk factors. The full model with all variables was estimated and then tested down using *z*- and joint-significance tests (Lagrange multiplier) to reveal the final model with the remaining statistically significant risk factors only. Though the presence or absence of some risk factors could be identified (transit stations, e.g.), census variables are continuous and were thus modified. One potential option would be to categorize variables based on standard deviations (SD); however, because many variables were non-normally distributed, such a categorization would generate strange results. As such, we chose to classify census and land-use variables into quartiles ranging from 0 to 3. Based on the negative binomial regression results and expectations, all variables were classified as representing increases in risk—except for recent immigration, postsecondary education, and median income, which ranged from −3 to 0.

Data were then used to generate four risk terrain surfaces. The first two were based on the full regression model, including all variables whether or not statistically significant; one included the 2011 residential burglary variable (transformed into quartiles) and the other did not. The second two were based on the final regression model, which included statistically significant variables only; one included the 2011 residential burglary variable and the other did not.

Results

Mapped residential burglary counts for 2011 and 2012 are shown in Fig. 1. Immediately obvious was that there were no high levels of concentration in either year. There was a statistically significant degree of spatial clustering in 2011 (Moran's $I = 0.275$) and 2012 (Moran's $I = 0.224$), with the presence of local hotspots using local Moran's I (maps available upon request) in areas with higher counts of single-family residential dwellings: southwestern and southeastern Vancouver. Residential burglary rates (per 1000 dwellings) reinforce this spatial pattern, leading to a more obvious spatial concentration in the southwestern portion of Vancouver: 2011 Moran's $I = 0.364$ and 2012 Moran's $I = 0.361$. From a theoretical perspective, considering the social disorganization theory, this is somewhat unexpected because it is one of the wealthiest areas, where one would expect more social organization. Furthermore, according to environmental criminology, it should be outside of offenders' awareness space, as offenders likely live in poorer neighborhoods away from these areas. However, these locations do represent more attractive/suitable targets because of the expected higher value of goods in households (Fig. 2).

Results of the negative binomial regression models used to identify statistically significant risk factors are presented in Table 2. As noted above, we include both the full model (all independent variables initially identified) and the final model (independent variables remaining after a general-to-specific testing method). For the full model, nine variables were statistically significant: number of dwellings, recent immigrants, visible minorities, unemployment rate, major repairs, median dwelling value, median income, two-family dwellings, and pawnbrokers. Generally speaking, all variables have their expected signs, with positive relationships being present for all risk factors except for recent immigrants and median income—as expected and discussed above. The final model retains all those variables plus second-hand dealers, which has a positive relationship with residential burglary. The overlap between the set of remaining statistically significant variables with the initial full model and the similarity of the magnitude of estimated parameters (which are never more than 1 SD different from each another in each model) provide confidence—in addition to the extensive statistical testing—that multicollinearity is not an issue in our models. As discussed above, we calculate risk terrain surfaces for both the full and final models with and without crime data.

Descriptive statistics for the four risk terrain surfaces are presented in Table 3. Because we used positive and negative risk factors, some DAs have negative risk values, which we retained rather than scaling risk values to begin with zero. The full model ranged from -1 to 32 in risk values when including 2011 residential burglaries but only to 30 when 2011 data were not included, though the latter model was still statistically significant. This shows that DAs with upper-quartile values for 2011 were, at least in some cases, in DAs with the highest risk values. Due to the lower number of risk factors, the final model has a lower range of actual risk values, ranging from -3 to 17 with 2011 residential burglaries and -4 to 16 without.

Risk terrain surfaces for the four different models are shown in Fig. 3. The full models with and without 2011 residential burglaries, Fig. 3a and b, respectively, show

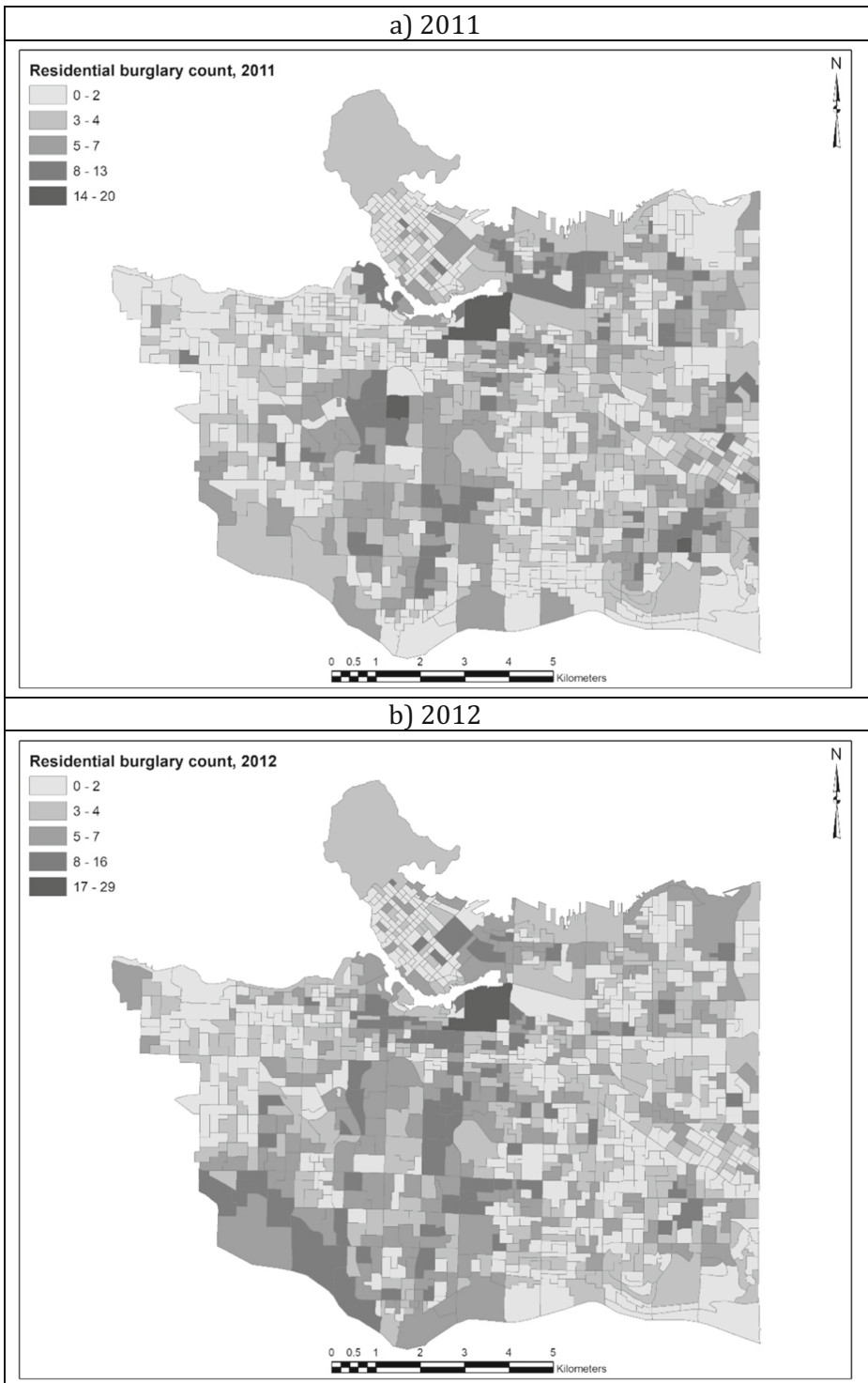


Fig. 1 Residential burglary counts, Vancouver, 2011 and 2012

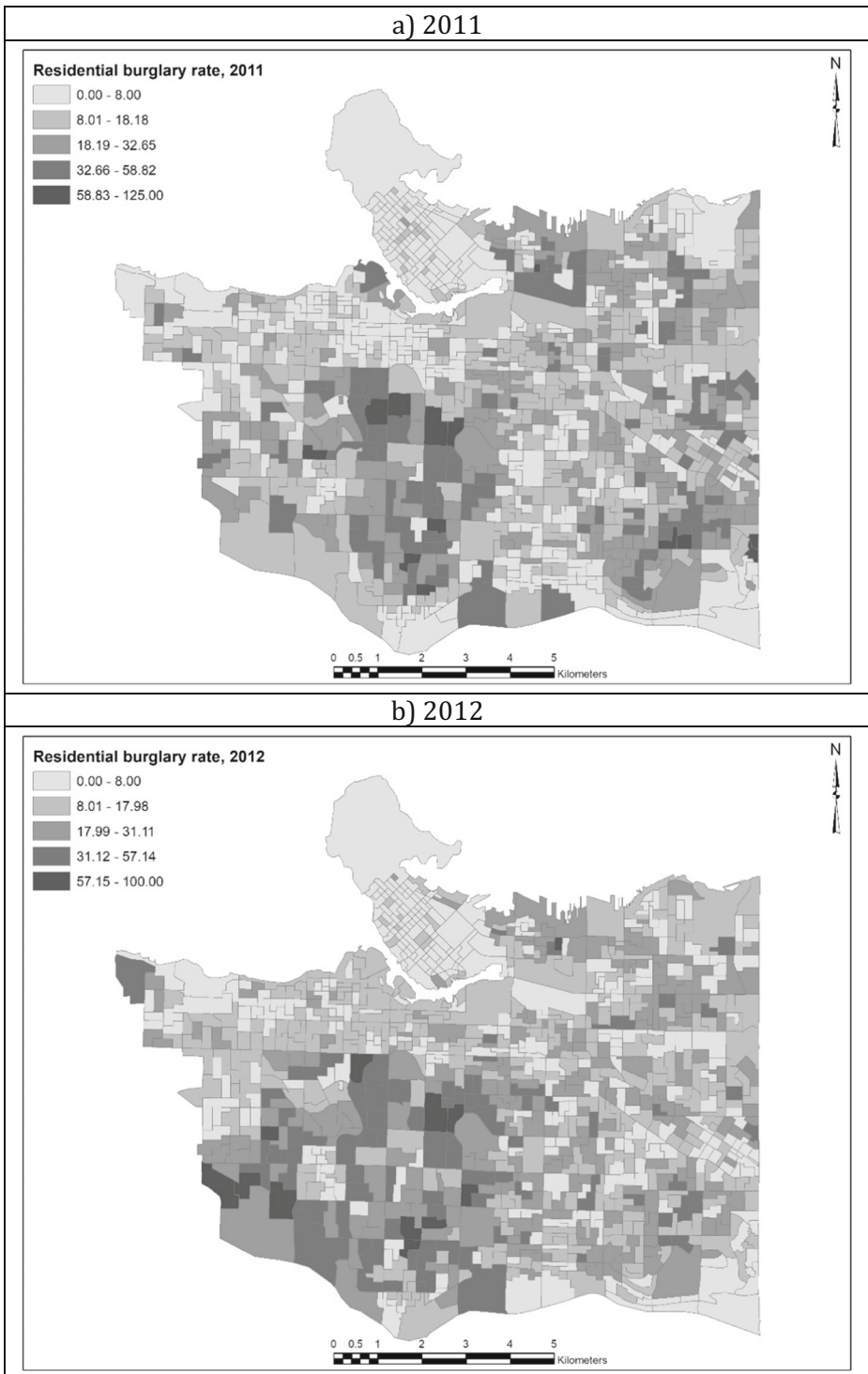


Fig. 2 Residential burglary rates, Vancouver, 2011 and 2012

Table 2 Negative binomial regression results, residential burglary, 2011

	Full model				Final model			
	Estimate	SE	RRR	P-value	Estimate	SE	RRR	P value
(Intercept)	0.942	0.320	2.566	< 0.01	0.673	0.189	1.961	< 0.01
Number of dwellings	0.001	0.000	1.001	< 0.01	0.001	0.000	1.001	< 0.01
Young men, %	-0.003	0.006	0.997	0.57				
Recent immigrants, %	-0.011	0.005	0.989	0.03	-0.012	0.005	0.988	0.01
Visible minorities, %	0.004	0.002	1.004	0.05	0.004	0.001	1.004	0.01
Mobility, 1 year, %	-0.001	0.004	0.999	0.88				
Postsecondary education, %	-0.002	0.002	0.998	0.53				
Unemployment rate	0.011	0.004	1.011	0.01	0.010	0.004	1.010	0.01
Public transportation, %	0.000	0.003	1.000	0.89				
Major repairs, %	0.007	0.003	1.007	0.02	0.007	0.003	1.007	0.02
Rentals, %	-0.001	0.001	0.999	0.46				
Median dwelling value, 000s \$	0.000	0.000	1.000	< 0.01	0.000	0.000	1.000	< 0.01
Median income, 000s \$	-0.012	0.000	0.988	< 0.01	-0.011	0.000	0.989	< 0.01
Government assistance, %	-0.004	0.005	0.996	0.34				
Skytrain stations	0.101	0.148	1.106	0.50				
Mixed land use, %	0.003	0.005	1.003	0.52				
Multifamily dwellings, %	0.000	0.023	1.000	0.99				
Two-family dwellings, %	0.042	0.015	1.043	< 0.01	0.039	0.014	1.040	0.01
Single-family dwellings, %	0.001	0.001	1.001	0.34				
Not-for-profit housing	0.058	0.047	1.059	0.22				
Pawnbrokers	0.218	0.132	1.244	0.10	0.269	0.123	1.309	0.03
Second-hand dealers	0.040	0.030	1.040	0.18	0.056	0.026	1.058	0.03

SE standard error, RRR relative risk ratio, 000s \$ amount in thousand dollars (CAD)

the same general pattern that would be expected in the context of social disorganization theory: risk is greater in the eastern and northeastern portion of Vancouver where income and wealth is lower, and lowest in the western portion which is within the wealthier areas. Though still present, this become less evident for the final models (Fig. 3c and d) because fewer social disorganization and routine activity theory variables are included. Statistically significant positive spatial autocorrelation is still present, but not to the same degree as in the full models.

Turning to the predictive power of the risk terrain surface for 2012: the full model shows a statistically significant relationship between risk value and number of 2012 residential burglaries: with a relative risk ratio (RRR) of 1.013, we expect a 1.3% increase with a one-unit increase in risk terrain surface value. Though a 1.3% change may be considered low, and is lower than found in other RTM contexts, risk terrain values have a large degree of variation, and our results are in the context of a count-based regression model, not a logistic regression analysis, indicating the presence or absence of residential burglaries in 2012. Curiously, when 2011 burglaries are removed from the risk surface, the predictive value of the risk terrain

Table 3 Descriptive statistics, risk terrain surfaces

	Minimum	Maximum	Mean	SD
Full model	-1	32	12.80	5.26
Full model, less crime	-1	30	11.54	4.99
Final model	-3	17	4.91	3.16
Final model, less crime	-4	16	3.64	2.75

SD standard deviation

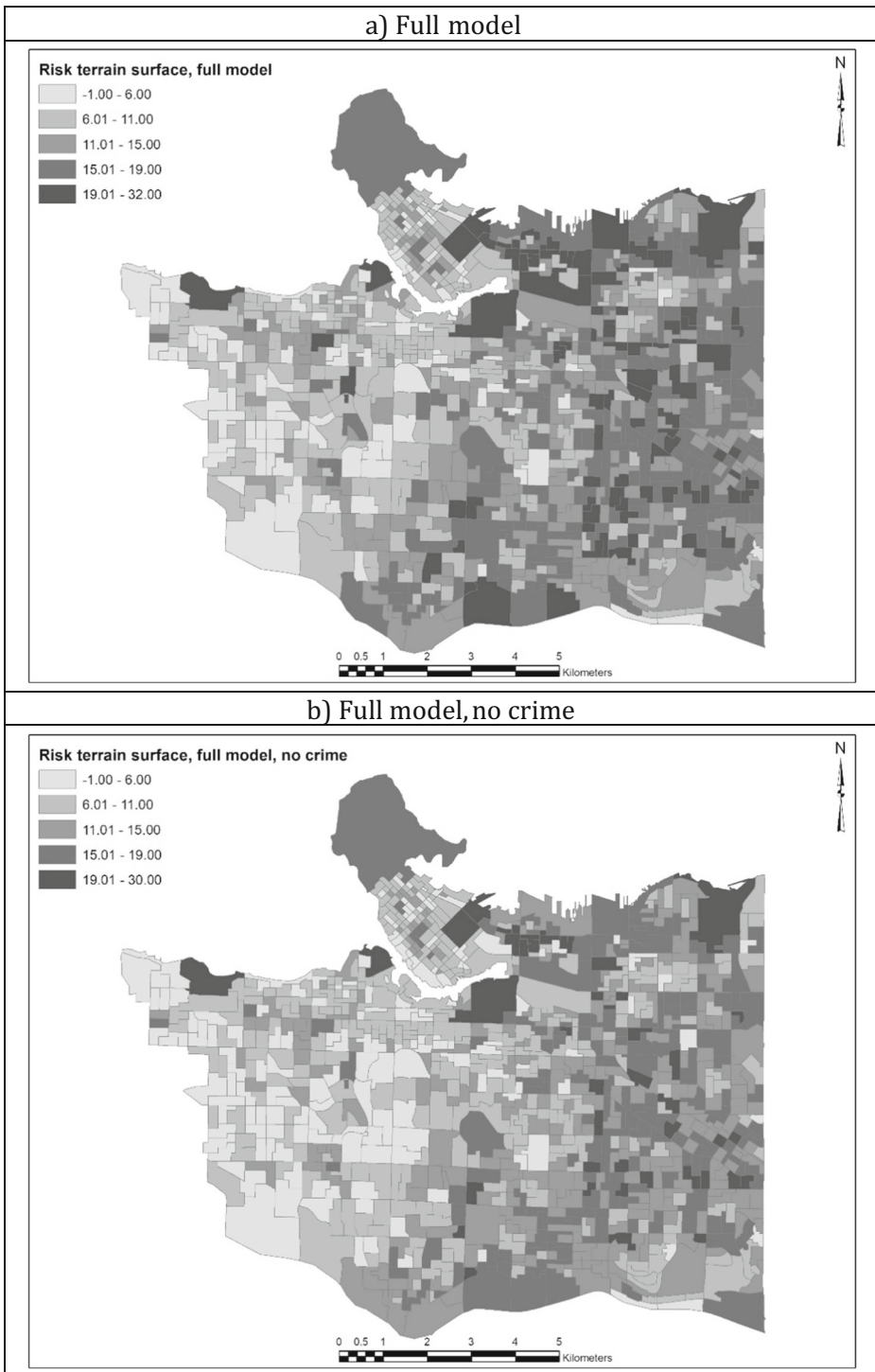


Fig. 3 Risk terrain surfaces, residential burglary, Vancouver

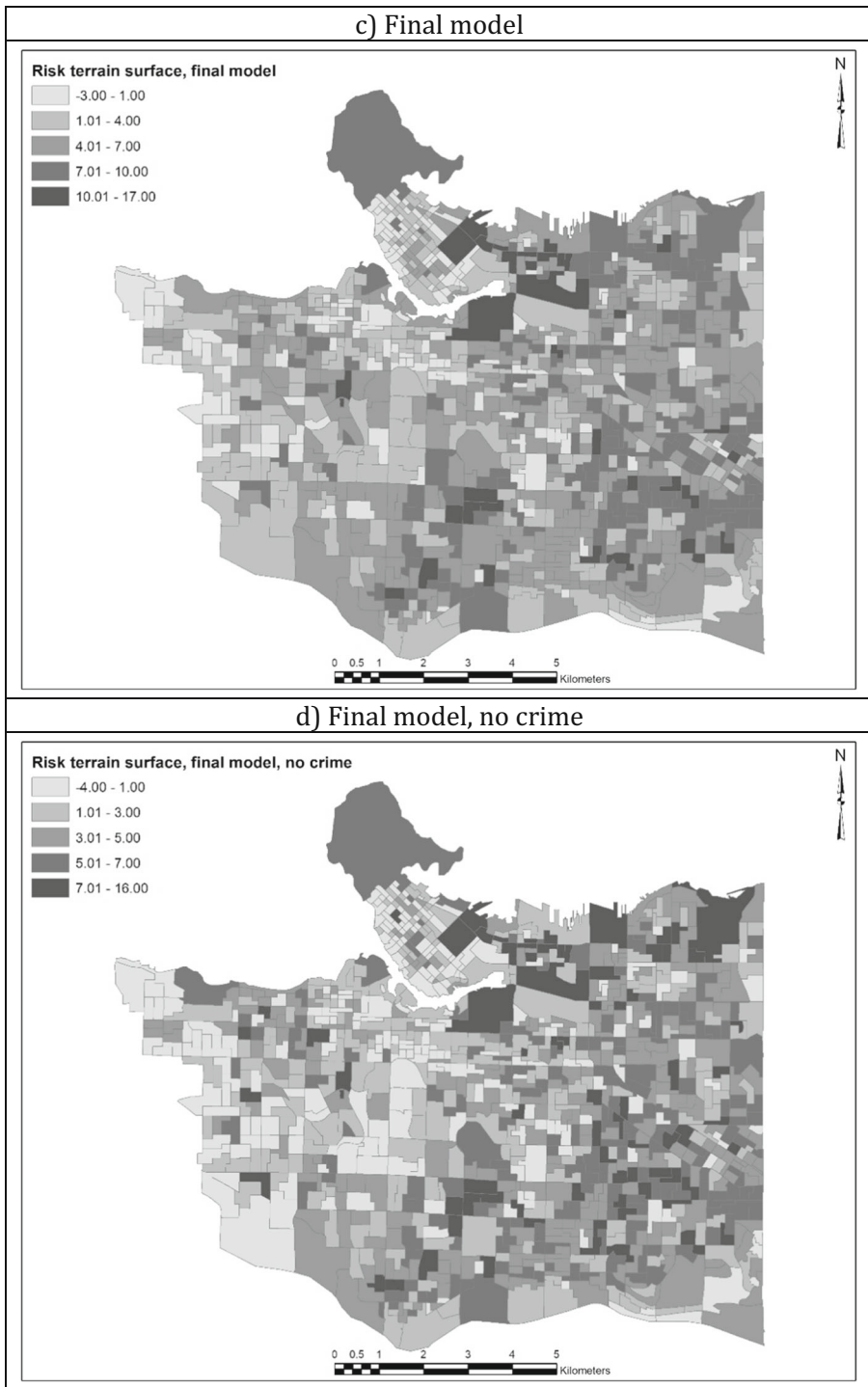


Fig. 3 (continued)

surface for 2012 becomes statistically insignificant, with a corresponding increase in the Akaike Information Criterion (AIC) value, indicating a poorer fit.

The results of the final models are more promising: The model including 2011 data shows a statistically significant and positive relationship between risk terrain value and 2012 data. Moreover, with an RRR of 1.051, a one-unit increase in risk terrain value is expected to increase residential burglaries by 5.1%. In the current context, this is a large impact. When 2011 data are removed, the relationship is still statistically significant but has lower estimated parameter: a 3.1% increase is expected from a one-unit increase in risk terrain value. It is also important to note that the AIC value are lower (better) for the final models when compared with their respective full models, and the final model with 2011 data has the lowest AIC value, indicating the best overall model fit (Table 4).

Discussion

The findings here support the applicability of RTM on residential burglary rates and support the need to include additional social ecological variables, at least in the Vancouver context. It is important to note that the risk surfaces generated differ from the actual pattern such rates. Risk terrain surfaces demonstrated a higher risk in east Vancouver, one of the poorest areas of the city, which encompasses the downtown east side, notoriously defined as “Canada’s poorest urban postal code” (Barnes and Sutton 2009). This area is the only known drug market in the city and experiences a number of social disorder issues. However, the highest levels of risk for residential burglary are in the western portion of Vancouver. Although the theoretically informed variables used to generate the risk terrain surface were statistically significant in the expected directions in our negative binomial model, the resulting risk terrain surface differs qualitatively from crime-rate maps. As such, though instructive in a regression context, care must be taken when applying such variables to RTM. Our findings suggest that while crime should theoretically be influenced by social disorganization variables, this may not be the case when analyzing particular types of crime. Specificity in variable selection is key when predicting different crime risks. This is consistent with a burgeoning crime-and-place literature and RTM literature, which illustrates the need to examine individual crime types and their correlates and specifies different risk factors for different crime types (Andresen and Linning

Table 4 Negative binomial regression results, risk terrain surfaces

	Estimate	SE	RRR	<i>P</i> value
(Intercept)	1.033	0.098	2.810	< 0.01
Full model	0.013	0.007	1.013	0.05
AIC: 4431.3				
(Intercept)	1.155	0.093	3.174	< 0.01
Full model, less crime	0.004	0.007	1.004	0.55
AIC: 4438.7				
(Intercept)	0.951	0.065	2.587	< 0.01
Final model	0.049	0.010	1.051	< 0.01
AIC: 4398.7				
(Intercept)	1.092	0.057	2.980	< 0.01
Final model, less crime	0.030	0.012	1.031	< 0.01
AIC: 4428.2				

AIC Akaike Information Criterion

2012). This becomes more evident in the final model, which has fewer variables and a better goodness of fit with the 2012 residential burglaries.

The final risk surface model included number of dwellings, recent immigrants, visible minorities, unemployment rate, major repairs, median dwelling value, median income, two-family dwellings, pawnbrokers, and second-hand dealers. Similarities emerge with this risk surface analysis and that reported by Moreto et al. (2014). For example, the presence of pawn brokers contributed to risk, and the presence of second-hand dealers was also a statistically significant variable in the model. Both locations provide suitable places to quickly transfer stolen items into cash.

Similar to Moreto et al. (2014), we found that land use contributed to the overall risk surface, though only partially. In our model, two-family dwellings and number of dwellings were statistically significant variables. This is not surprising, as they represent residential land use and, in turn, the presence of opportunities. Surprisingly, however, single-unit dwellings, the most form of common land use in Vancouver, did not emerge as statistically significant in the final model. This could be a result of the lack of variation in the values for single-unit dwellings across DAs in Vancouver.

Interestingly, some additional variables emerged as significant that were not present in Moreto et al.'s (2014) model. For example, the higher the median value of a dwelling in an area, the greater the risk; the higher the median income of an area, the lower the risk. While this appears counterintuitive, it is possible that offenders may break into houses that appear wealthier and may have better targets; however, homeowners in DAs with a greater median income may be able to better afford security measures that deter these incidents. Unemployment rate also emerged as a statistically significant, and positive, risk factor for residential burglary.

Finally, risk surface also included recent immigrants and visible minorities: the more recent immigrants in an area, the lower the risk; the minorities visible in an area, the greater the risk. Again, while seemingly incongruent, immigration in Vancouver includes predominately wealthy immigrants who settle in neighborhoods with higher socioeconomic status (Andresen 2006; Ley 1999; Ley and Smith 2000) and will likely be able to afford better security technologies. However, the rate of visible minorities increasing the risk of burglary is consistent with ethnic heterogeneity as a correlate of crime in the social disorganization theory.

Inconsistent with Moreto et al. (2014) is the insignificance of transportation nodes in our model. Previous research found statistically significant relationships between public transportation and crime, including residential burglary (Loukaitou-Sideris et al. 2002; Sedelmaier 2014; Gallison and Andresen 2017). Specific to Vancouver, the Skytrain system has a reputation as a crime generator and/or attractor, being dubbed the "crime train" (Bennett 2008). This is important to note because the presence of such a train station is not necessarily a contributing factor to local criminal activity, particularly in the context of residential burglary.

As noted above, findings from crime rate maps show a greater risk of burglary on the western of Vancouver. This is not particularly surprising considering that the most expensive housing is found in this location and targets would be the most desirable. Surprisingly, however, one would expect these homes to be equipped with the most advanced security technology, as residents can likely afford it. This would be consistent with the security hypothesis as proposed by Farrell et al. (2011), which argues that increases in security contributed to decreases in property crime. However, this does not appear to be the case in Vancouver. This could in part be because these locations do not have security (such data is not readily available). It could also indicate that the security hypothesis does not translate to home alarm technologies, which may draw attention to the offender but may not actually prevent

them from entering the home. Alternatively, this could be an indirect result of security improvements. For example, Vancouver has become denser residentially, largely a result of geographical constraints (ocean on one side and mountains on the other) preventing typical urban sprawl. The city is also quickly becoming one of the most expensive housing markets in the country and the third most expensive in the world.¹⁰ Thus, as the city increases in population density and cost of housing, single-family homes are no longer feasible for most people, and residential towers have been built. These towers often have advanced security protocols, including front-door key fobs, floor-specific key fobs, and—on rare occasions—lobby security. Thus, high-density-population buildings should be more difficult to enter from the street and have fewer points of entry for an offender, making them less desirable and more difficult to burglarize. For a number of reasons, the east side of the city is quickly becoming more densely populated.¹¹ Thus, it is possible that the west side is at greater risk because it is less densely populated and comprises more single-family or multi-family homes with more entry points. In this case, the security hypothesis would be appropriate.

This discussion, though in the specific context of residential burglary and RTM, has broader implications for the broader RTM literature. RTM is typically implemented considering risk factors at the point level and then aggregated to a relatively small grid, as discussed above. Though the spatial units of analysis employed in this study are larger than the standard grid cells (just over twice the size, on average), statistically significant insight has been garnered that would not have been possible had census boundaries not been considered. The result that DAs are shown to be important should be expected given recent research in the crime-and-place literature that considers the variability in spatial crime patterns, which can be explained at the micro-place (street-segment) level. As shown by Steenbeek and Weisburd (2016) and Schnell et al. (2017), micro-place analysis accounts for ~60% of variation in spatial crime patterns. Though 60% of the variation is a large proportion of spatial crime patterns, emphasizing the importance of the micro-place not only in the crime-and-place literature but the use of point-level risk factors in RTM, 40% of that spatial pattern variation is explained in larger areas: neighborhoods and communities/districts. Ignoring these larger area risk factors may impose bias on results, including on a risk terrain surface. It is important for the larger RTM literature to consider theoretically informed area-based risk factors that can be identified in the census and allows for the application of RTM at a variety of spatial scales for sensitivity analyses.

This study has limitations. First, some variables that could contribute to the risk of residential burglary could not be included because they cannot be made binary, which is a necessity for this type of modeling. For example, offender socioeconomic status would likely be correlated with residential burglaries (Rengert and Wasilchick 1985). However, unless the offender is caught, obtaining data on offender income is unlikely. Furthermore, socioeconomic status of a neighborhood should logically contribute to residential burglary risk, i.e., neighborhoods with higher incomes would be more attractive to offenders, as they would likely contain items of higher value. However, much of the research shows that offenders tend to offend where they live because they have intimate knowledge of that space (Rengert and Wasilchick 1985) and journey to the crime scene is rather short (Andresen et al. 2014). The second study limitation is that we do not know the location of offenders' homes. This knowledge would address the point just made: the journey to the crime scene is short. Thus, offenders are likely to offend, and reoffend, in homes that are close to their residences (Bennett and Wright 1984; Forrester et al. 1988; Wright and Decker 1994; Bernasco and Nieuwbeerta 2005;

¹⁰ <https://beta.theglobeandmail.com/real-estate/vancouver/vancouver-housing-market-third-most-expensive-in-the-world-survey/article33702895/?ref=http://www.theglobeandmail.com&>

¹¹ https://cityhallwatch.wordpress.com/2013/08/26/eastside_population/

Bernasco 2006; Kleemans 2001). Finally, there is the modifiable area unit problem. We used larger areas (DAs) for creating the risk terrain surface than previous research (usually 50 m² grids). Though the use of DAs is appropriate in the context of our study because of the nature of our data (measured at the level of a census geography), this may be why our results were not as expected. However, to avoid the ecological fallacy (Robinson 1950; Openshaw 1984a), we maintained the census-level geography. It is important to note that issues emerging from the modifiable area unit problem may be present (Fotheringham and Wong 1991; Openshaw 1984b).

Conclusion

We expand upon the residential burglary research by Moreto et al. (2014) specifically and contribute to the relatively small body of RTM literature that has investigated property crime. We show the importance of considering additional variables, specifically those related to socioeconomic status and ethnic heterogeneity; in short, social ecological variables are important for understanding residential burglary. Not only does this expand on the findings from Moreto et al. (2014) but could also have important implications for future RTM research as the field expands. While examining risk at the micro-level is important, larger social structural factors cannot be ignored. Due to the specific nature of the risk factors identified in our regression models, we find support for the RTM literature using risk factors specific to crime types. We have added a much-needed Canadian context to the RTM literature, adding to the generalizability of this technique in crime analysis.

References

- Andresen, M. A. (2006). A spatial analysis of crime in Vancouver, British Columbia: a synthesis of social disorganization and routine activity theory. *Canadian Geographer*, 50(4), 487–502.
- Andresen, M. A. (2011a). Estimating the probability of local crime clusters: the impact of immediate spatial neighbors. *Journal of Criminal Justice*, 39(5), 394–404.
- Andresen, M. A. (2011b). The ambient population and crime analysis. *The Professional Geographer*, 63(2), 193–212.
- Andresen, M. A. (2014). *Environmental criminology: Evolution, theory, and practice*. New York: Routledge.
- Andresen, M. A., & Linning, S. J. (2012). The (in)appropriateness of aggregating across crime types. *Applied Geography*, 35(1–2), 275–282.
- Andresen, M. A., Frank, R., & Felson, M. (2014). Age and the distance to crime. *Criminology & Criminal Justice*, 14(3), 314–333.
- Andresen, M. A., Linning, S. J., & Malleon, N. (2017). Crime at places and spatial concentrations: Exploring the spatial stability of property crime in Vancouver BC, 2003–2013. *Journal of Quantitative Criminology*, 33(2), 255–275.
- Armitage, R. (2013). *Crime prevention through housing design: Policy and practice*. Basingstoke: Palgrave Macmillan.
- Armitage, R., & Joyce, C. (2016). “Why my house?”—Exploring the influence of residential housing design on burglar decision making. New York: Routledge.
- Barnes, T., & Sutton, T. (2009). Situating the new economy: contingencies of regeneration and dislocation in Vancouver’s inner city. *Urban Studies*, 46(5–6), 1247–1269.
- Barnum, J. D., Caplan, J. M., Kennedy, L. W., & Piza, E. L. (2017). The crime kaleidoscope: a cross-jurisdictional analysis of place features and crime in three urban environments. *Applied Geography*, 79, 203–211.
- Bennett, N. (2008). SkyTrain crime anticipated. *The Vancouver Sun*, 15 January 2008, p. B2.
- Bennett, T., & Wright, R. (1984). *Burglars on burglary*. Brookfield: Gower Publishing.
- Bernasco, W. (2006). Co-offending and the choice of target areas in burglary. *Journal of Investigative Psychology and Offender Profiling*, 3(3), 139–155.
- Bernasco, W., & Nieuwbeerta, P. (2005). How do residential burglars select target areas? A new approach to the analysis of criminal location choice. *British Journal of Criminology*, 45(1), 296–315.
- Braga, A. A., & Clarke, R. V. (2014). Explaining high-risk concentrations of crime in the city. *Journal of Research in Crime and Delinquency*, 51(4), 480–498.

- Brantingham, P. L., & Brantingham, P. J. (1981). Notes on the geometry of crime. In P. J. Brantingham & P. L. Brantingham (Eds.), *Environmental criminology* (pp. 27–54). Waveland Press: Prospect Heights IL.
- Brantingham, P. L., & Brantingham, P. J. (1993). Environment, routine, and situation: Toward a pattern theory of crime. In R. V. Clarke & M. Felson (Eds.), *Routine activity and rational choice, volume 5* (pp. 259–294). New Brunswick: Transaction publishers.
- Brantingham, P. L., & Brantingham, P. J. (1995). The criminality of place: Crime generators and crime attractors. *European Journal on Criminal Policy and Research*, 3(3), 5–26.
- Caplan, J. M., & Kennedy, L. W. (2013). *Risk terrain modeling diagnostics utility (version 1.0)*. Newark: Rutgers Center on Public Security.
- Caplan, J. M., Kennedy, L. W., & Miller, J. (2011). Risk terrain modeling: Brokering criminological theory and GIS methods for crime forecasting. *Justice Quarterly*, 28(2), 360–381.
- Caplan, J. M., Kennedy, L. W., & Piza, E. L. (2013). Joint utility of event-dependent and environmental crime analysis techniques for violent crime forecasting. *Crime & Delinquency*, 59(2), 243–270.
- Clare, J., Fernandez, J., & Morgan, F. (2009). Formal evaluation of the impact of barriers and connectors on residential burglars' macro-level offending location choices. *Australian and New Zealand Journal of Criminology*, 42(2), 139–158.
- Clarke, R. V., & Cornish, D. B. (1985). Modeling offenders' decisions: a framework for research and policy. *Crime and Justice*, 6, 147–185.
- Cohen, L. E., & Felson, M. (1979). Social change and crime rate trends: a routine activity approach. *American Sociological Review*, 44(4), 588–608.
- Cozens, P., & Love, T. (2015). A review and current status of crime prevention through environmental design (CPTED). *Journal of Planning Literature*, 30(4), 393–412.
- Cozens, P.M., Saville, G., & Hillier, D. (2005). Crime prevention through environmental design (CPTED): a review and modern bibliography. *Property Management*, 23(5), 328–356.
- Cromwell, P. F., Olson, J. N., & Avary, D. W. (1991). *Breaking and entering: An ethnographic analysis of burglary*. Newbury Park: Sage Publications.
- Crowe, T.D. (2000). *Crime prevention through environmental design (2nd edition)*. Boston, MA: Butterworth-Heinemann.
- Curman, A. S. N., Andresen, M. A., & Brantingham, P. J. (2015). Crime and place: a longitudinal examination of street segment patterns in Vancouver, BC. *Journal of Quantitative Criminology*, 31(1), 127–147.
- Davies, G. (2006). *Crime, neighborhood, and public housing*. El Paso: LFB Scholarly Publishing LLC.
- Farrell, G., & Pease, K. (1993). *Once bitten, twice bitten: Repeat victimization and its implications for crime prevention*. London: Police Research Group, Home Office.
- Farrell, G., Phillips, C., & Pease, K. (1995). Like taking candy: why does repeat victimization occur? *British Journal of Criminology*, 35(3), 384–399.
- Farrell, G., Tseloni, A., Mailley, J., & Tilley, N. (2011). The crime drop and the security hypothesis. *Journal of Research in Crime and Delinquency*, 48(2), 147–175.
- Felson, M., & Eckert, M. (2016). *Crime and everyday life* (5th ed.). Los Angeles: Sage Publications.
- Forrester, D., Chatterton, M., & Pease, K. (1988). *The Kirkholt burglary prevention project, Rochdale*. Home Office Crime Prevention Unit, Paper 13. London: Home Office.
- Fotheringham, A. S., & Wong, D. W. S. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A*, 23(7), 1025–1044.
- Gallison, J. K., & Andresen, M. A. (2017). Crime and public transportation: a case study of Ottawa's O-Train system. *Canadian Journal of Criminology and Criminal Justice*, 59(1), 94–122.
- Groff, E. R., & La Vigne, N. G. (2001). Mapping an opportunity surface of residential burglary. *Journal of Research in Crime and Delinquency*, 38(3), 257–278.
- Groff, E. R., Weisburd, D., & Yang, S.-M. (2010). Is it important to examine crime trends at a local "micro" level? A longitudinal analysis of street to street variability in crime trajectories. *Journal of Quantitative Criminology*, 26(1), 7–32.
- Hirschi, T., & Gottfredson, M. (1983). Age and the explanation of crime. *American Journal of Sociology*, 89(3), 552–584.
- Johnson, S. D., & Bowers, K. J. (2004). The burglary as clue to the future: the beginnings of prospective hot-spotting. *European Journal of Criminology*, 1(2), 237–255.
- Johnson, S. D., Bernasco, W., Bowers, K. J., Elffers, H., Ratcliffe, J., Rengert, G., & Townsley, M. (2007). Space-time patterns of risk: a cross-national assessment of residential burglary victimization. *Journal of Quantitative Criminology*, 23(3), 201–219.
- Johnson, S. D., Summers, L., & Pease, K. (2009). Offender as forager? A direct test of the boost account of victimization. *Journal of Quantitative Criminology*, 25(2), 181–200.
- Kennedy, L. W., & Forde, D. R. (1990). Routine activities and crime: An analysis of victimization in Canada. *Criminology*, 28(1), 137–152.

- Kennedy, L. W., Caplan, J. M., & Piza, E. (2011). Risk clusters, hotspots, and spatial intelligence: Risk terrain modeling as an algorithm for police resource allocation strategies. *Journal of Quantitative Criminology*, 27(3), 339–362.
- Kennedy, L. W., Caplan, J. M., Piza, E. L., & Buccine-Schraeder. (2016). Vulnerability and exposure to crime: applying risk terrain modeling to the study of assault in Chicago. *Applied Spatial Analysis and Policy*, 9(4), 529–548.
- Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., & Brantingham, P. J. (2008). Crime attractors, generators and detractors: land use and urban crime opportunities. *Built Environment*, 34(1), 62–74.
- Kleemans, E. R. (2001). Repeat burglary victimization: Results of empirical research in the Netherlands. In G. Farrell & K. Pease (Eds.), *Repeat victimization* (pp. 53–68). Monsey: Criminal Justice Press.
- Ley, D. (1999). Myths and meanings of immigration and the metropolis. *Canadian Geographer*, 43(1), 2–19.
- Ley, D., & Smith, H. (2000). Relations between deprivation and immigrant groups in large Canadian cities. *Urban Studies*, 37(1), 37–62.
- Loukaitou-Sideris, A., Liggett, R., & Iseki, H. (2002). The geography of transit crime: documentation and evaluation of crime incidence on and around the green line stations in Los Angeles. *Journal of Planning Education and Research*, 22(2), 135–151.
- Lowenkamp, C. T., Cullen, F. T., & Pratt, T. C. (2003). Replicating Sampson and Groves's test of social disorganization theory: revisiting a criminological classic. *Journal of Research in Crime and Delinquency*, 40(4), 351–373.
- MacDonald, J. M., Hipp, J. R., & Gill, C. (2013). The effects of immigrant concentration on changes in neighborhood crime rates. *Journal of Quantitative Criminology*, 29(2), 191–215.
- Mawby, R. I. (2001). *Burglary*. Portland: Willan Publishing.
- Moreto, W. D., Piza, E. L., & Caplan, J. M. (2014). "A plague on both your houses?": risks, repeats and reconsiderations of urban residential burglary. *Justice Quarterly*, 31(6), 1102–1126.
- Openshaw, S. (1984a). Ecological fallacies and the analysis of areal census data. *Environment and Planning A*, 16(1), 17–31.
- Openshaw, S. (1984b). *The modifiable areal unit problem. CATMOG (concepts and techniques in modern geography)* 38. Norwich: Geo Books.
- Rengert, G. F., & Wasilchick, J. (1985). *Suburban burglary: A time and a place for everything*. Springfield: Charles C. Thomas.
- Reynald, D. M. (2011). Factors associated with the guardianship of places: assessing the relative importance of the spatio-physical and sociodemographic contexts in generating opportunities for capable guardianship. *Journal of Research in Crime and Delinquency*, 48(1), 110–142.
- Robinson, W. S. (1950). Ecological correlations and the behavior of individuals. *American Sociological Review*, 15(3), 351–357.
- Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: testing social-disorganization theory. *American Journal of Sociology*, 94(4), 774–802.
- Schnell, C., Braga, A. A., & Piza, E. L. (2017). The influence of community areas, neighborhood clusters, and street segments on the spatial variability of violent crime in Chicago. *Journal of Quantitative Criminology*, 33(3), 469–496.
- Sedelmaier, C. M. (2014). Offender-target redistribution on a new public transport system. *Security Journal*, 27(S2), 164–1791.
- Shaw, C. R., & McKay, H. D. (1931). *Social factors in juvenile delinquency*. Washington, DC: U.S. Government Printing Office.
- Shaw, C. R., & McKay, H. D. (1942). *Juvenile delinquency and urban areas: A study of rates of delinquency in relation to differential characteristics of local communities in American cities*. Chicago: University of Chicago Press.
- Shaw, C. R., Zorbaugh, F., McKay, H. D., & Cottrell, L. S. (1929). *Delinquency areas: A study of the geographic distribution of school truants, juvenile delinquents, and adult offenders in Chicago*. Chicago: University of Chicago Press.
- Sherman, L. W., Gartin, P. R., & Buerger, M. E. (1989). Hot spots of predatory crime: routine activities and the criminology of place. *Criminology*, 27(1), 27–55.
- Stansfield, R., Akins, S., Rumbaut, R. G., & Hammer, R. B. (2013). Assessing the effects of recent immigration on serious property crime in Austin, Texas. *Sociological Perspectives*, 56(4), 647–672.
- Steenbeek, W., & Weisburd, D. (2016). Where the action is in crime? An examination of variability of crime across different spatial units in the Hague, 2001–2009. *Journal of Quantitative Criminology*, 32(3), 449–469.
- Townsley, M., Homel, R., & Chaseling, J. (2003). Infectious burglaries: a test of the near repeat hypothesis. *British Journal of Criminology*, 43(3), 615–633.
- Waller, I. (1979). *Men released from prison*. Toronto: Centre of Criminology, University of Toronto.
- Waller, I. (2010). *Rights for victims of crime: Rebalancing justice*. Chicago: Rowman & Littlefield Publishers.
- Weisburd, D. (2015). The law of crime concentration and the criminology of place. *Criminology*, 53(2), 133–157.

- Weisburd, D., & Amram, S. (2014). The law of concentrations of crime at place: the case of Tel Aviv-Jaffa. *Police Practice and Research, 15*(2), 101–114.
- Weisburd, D., Bushway, S., Lum, C., & Yang, S.-M. (2004). Trajectories of crime at places: a longitudinal study of street segments in the City of Seattle. *Criminology, 42*(2), 283–321.
- Weisburd, D., Wyckoff, L. A., Ready, J., Eck, J. E., Hinkle, J. C. & Gajewski, F. (2006). Does crime just move around the corner? A controlled study of spatial displacement and diffusion of crime control benefits. *Criminology, 44*(3), 549–591.
- Wilson, J. Q., & Kelling, G. L. (1982). Broken windows. *Atlantic Monthly, 249*(3), 29–38.
- Wright, R. T., & Decker, S. H. (1994). *Burglars on the job*. Boston: Northeastern University Press.