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RESEARCH ARTICLE

Predictive crime mapping

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Geographic Information Systems (GIS) have emerged as a key tool in intelligence-led policing and spatial predictions of crime are being used by many police services to reduce crime. Break and entries (BNEs) are one of the most patterned and predictable crime types, and may be particularly amendable to predictive crime mapping. A pilot project was conducted to spatially predict BNEs and property crime in Vancouver, Canada. Using detailed data collected by the Vancouver Police Department on where and when observed crimes occur, the statistical model was able to predict future BNEs for residential and commercial locations. Ideally implemented within a mobile GIS, the automated model provides continually updated predictive maps and may assist patrol units in self-deployment decisions. Future research is required to overcome computational and statistical limitations, and to preform model validation.

Keywords: break and entries (BNEs); predictive mapping; Geographic Information Systems (GIS); intelligence led policing; Vancouver; statistical modeling

Introduction

Intelligence-led policing is a growing discipline where data, analysis, and criminal theory are used to guide police allocation and decision-making (Ratcliffe, 2012). Given that crime occurs within a geographical context that includes both space and time, information to support intelligence-led policing is increasingly map-based and can benefit from platforms that allow integration with Geographic Information Systems (GIS) (Chainey & Ratcliffe, 2005). Developments in mobile GIS technology (Tsou & Kim, 2010) are providing new opportunities for spatially explicit approaches to intelligence-led policing. For example, mapping of mobile phone calls and cell towers has enabled mobile GIS to be used to track perpetrators (Saravanan, Thayyil, & Narayanan, 2013). Another example of mobile GIS systems used for policing is mobile mapping systems installed in police vehicles that are providing patrol units with near real-time information on crime patterns (Wang, 2012).

In some regions, spatial predictions of crime are already being used by police to reduce crime. For example, the Los Angeles Police Department has used spatial predictions of crime to preemptively allocate patrol units and have estimated that geographical criminal intelligence have decreased violent crimes by 5.4% and homicides by 22.6% (Uchida et al., 2012). Similarly, identifying and policing crime hot spots has significantly reduced calls for service throughout the regions of Minneapolis (Sherman & Weisburd, 1995), Jersey City (Braga et al., 1999; Weisburd & Green, 1995), and Kansas

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City (Sherman et al., 1995) for a variety of offences including drug, violent, and property crimes.

Break and entries (BNEs) are one of the most patterned and predictable crime types (Short, Brantingham, Bertozzi, & Tita, 2010; Short, D'Orsogna, Brantingham, & Tita, 2009). For example, it has been observed that the probability of a repeat offence increases for the subsequent weeks and for the homes near the original BNE site (Short et al., 2009, 2010). Knowledge acquired during the original BNE regarding possessions, entry, and escape, make nearby homes 'easy' targets (Short et al., 2009; Wright & Decker, 1994) that often lead to localized hot spots of property crimes (Farrell, 1995; Johnson et al., 2007; Short & Hestbeck, 1995).

The goal of this paper is to present results from a pilot project to spatially predict property crime in Vancouver, Canada. The model was used to predict crime six times per day, at 4-h intervals, and outputs were designed to integrate with mobile mapping systems that provide maps and statistics of observed crime trends to patrol units. Models were generated using the Vancouver Police Districts (VPD) data on crime as well as additional data on the urban and human environment. To inform the model, we began with exploratory analysis that examined the space–time patterns of BNEs across Vancouver between 2001 and 2012. Based on the results of the exploratory analysis, separate models were developed for commercial and residential properties.

Study area and data

Vancouver is a metropolitan city housing more than 2.3 million residents and 22 neighborhoods (City of Vancouver, 2011) (see Figure 1).

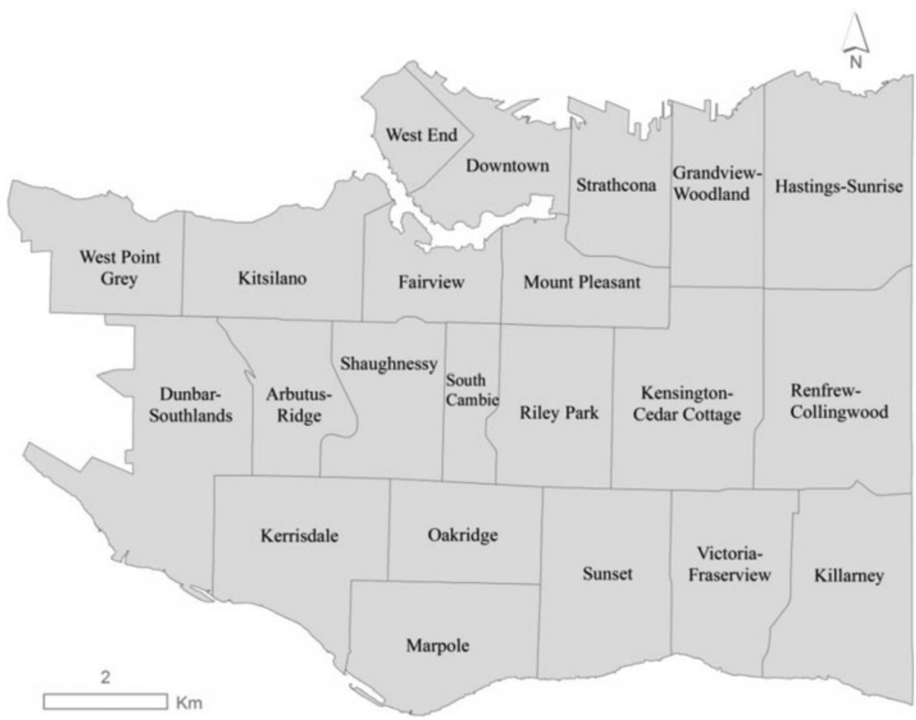

Figure 1. Study area. Vancouver, British Columbia, Canada divided by neighborhood. Neighbourhood delineations obtained from http://www.vancouver.ca/your-government/open-data-catalogue.aspx.

The majority of the population resides in the West End and Downtown proper surrounded by English Bay and Burrard Inlet. Lifestyles span from suburban single-family dwellings to high-rise living in the Downtown, West End, and West Point Grey areas; however all regions, with the exclusion of city parks, are highly urbanized offering many opportunities for break and entry offences (City of Vancouver, 2011). There were over 1.4 million property crimes recorded in the Vancouver metropolitan region between 2002 and 2011 (BC Ministry of Justice, 2012).

Crime data

To predict the spatial and temporal patterns of property crimes, we used point occurrence residential and commercial BNEs data from 2001 to 2012. These data were provided by the Vancouver Police Department's PRIME database. Attributes included *x*, *y* coordinate locations, reported crime category, and estimated time and date of occurrence. Crime data were converted to binary grids. To enable map-based prediction of crime probabilities six times per day (1:00–4:00, 5:00–8:00, 9:00–12:00, 13:00–16:00, 17:00–20:00, 21:00–23:00), crime data were formatted as presence/absence grids for six 4-h time intervals using a 200 m by 200 m grid of 3014 cells (see Figure 2).

The transformation resulted in 6,618,744 possible space–time locations for BNE occurrences. A value of one in the grid cell indicated break and entry occurrence, while zero indicated crime absence.

Urban and human environment data

Beyond the pattern of past crime, space–time patterns of future crime were related to the distributions of people, properties, and property types. Several data-sets on the urban

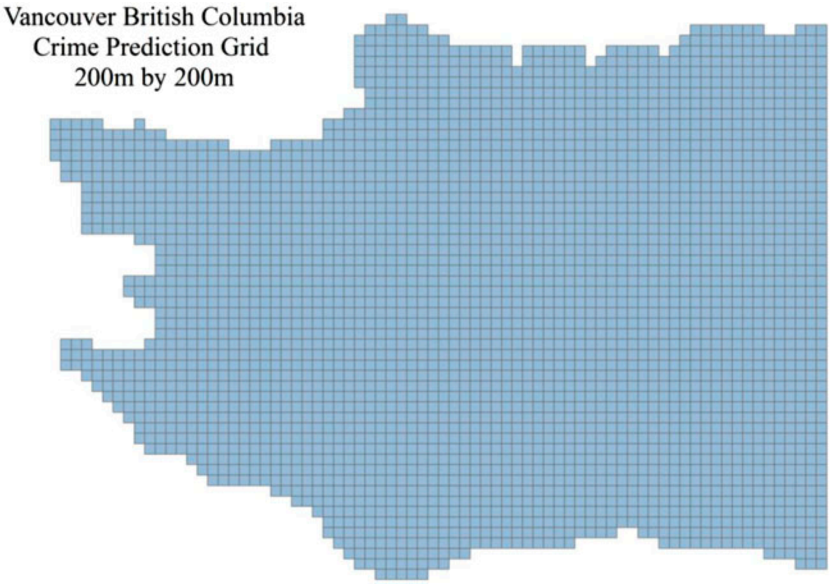

Figure 2. The study area divided into a crime prediction grid with each cell measuring 200 m by 200 m.

environment and socio-demographics were integrated into the models. To control for variations in crime associated with variance in population density (Hipp & Roussell, 2013), we used 2011 census dissemination block population estimates (see Figure 3(a)) and LandScan ambient population data (see Figure 3(b), which represent human activity patterns. The urban environment was represented using the national road network of primary and secondary roadways available from the GeoBase data repository (http://www.geobase.ca) (see Figure 3(c)) and street light density (Figure 3(d)), which is a measure of how urban an area is.

The density of a road network can indicate land use type in addition to transportation access for escape and potential sightings of perpetrators (Andresen, 2005). Criminologists have established that property types (Lens, 2013) and value (Pope & Pope, 2012) are key indicators of break and entry risk along with perceived ‘lawlessness’ of an area (Wilson & Kelling, 1982). To represent social instability, we used point graffiti data collected by municipal workers of the city of Vancouver available on from Vancouver’s open data license (http://vancouver.ca/your-government/open-data-catalogue.aspx) (see Figure 4).

Research-restricted municipal tax information also supplied information on the average property values, number of residential and commercial properties, and the dominant housing types across Vancouver (see Figures 5(a)–(d) and 6). All data were formatted into the same 200 m by 200 m grid format as the crime data.

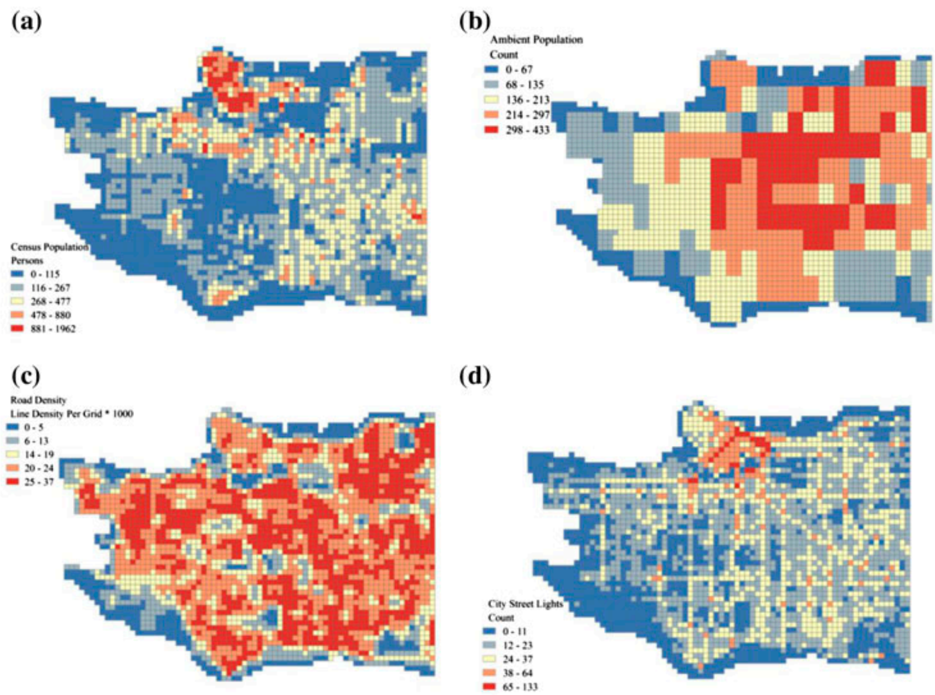

Figure 3. Vancouver’s demographic and amenity information. Map (a) displays the disaggregated census population count, map (b) the ambient population, and maps (c) and (d) display the road density and streetlight count per 200 m grid.

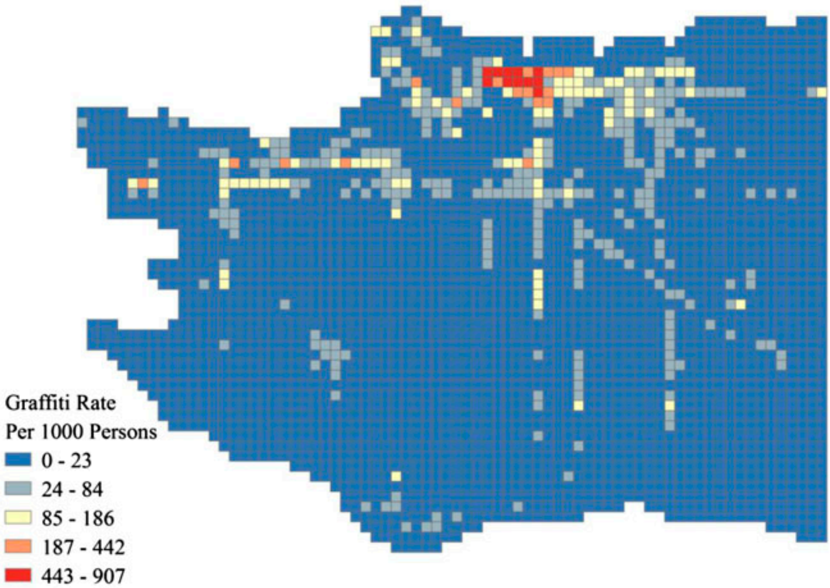

Figure 4. Vancouver's graffiti rate by 200 m grid cell.

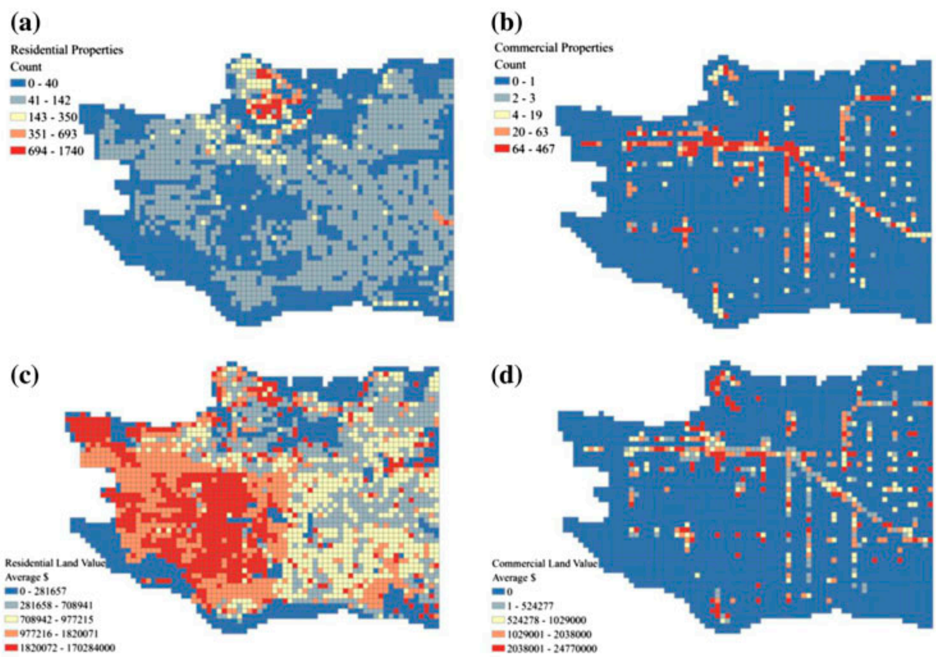

Figure 5. Vancouver's property information derived from geocoded municipal tax information. Maps (a) and (b) display the number and land values of the residential properties across Vancouver, while maps (c) and (d) display the commercial property counts and values.

Methods

Summarizing patterns in observed BNEs

Prior to modeling, we analyzed the space–time dynamics of BNEs. First we conducted frequency graphing of residential and commercial break-ins by hour, day, month, and year from 2001 to 2012 to illuminate trends in criminal behavior. Subsequent to analysis through time, we used density mapping (see O'Sullivan & Unwin, 2010 for method detail) of BNEs from 2001 to 2012 to examine spatial patterns and locate BNE hot spots.

In order to build associations through space and time into the model, we needed to characterize space–time clustering of BNE events. We employed Ratcliffe's (2009) near-repeat calculator to measure the spatial and temporal distance between each residential and commercial crime event that occurred. We assessed residential and commercial BNEs that were within 500, 850, and 1000 m from the originating event and from one day up to 30 days since the event occurred. Observed patterns were compared to random patterns to determine if the pattern of repeat or near repeat offences was significantly different from random.

Predicting future BNEs

Separate predictive models were developed for residential and commercial crimes, as crimes separated by property type had different observed patterns. We also built two models for each property type. Model 1 (Residential and Commercial) was based on integrating crime data and with ancillary data on the urban and human environment (see Table 1), in a regression model (generalized linear logistic regression models with

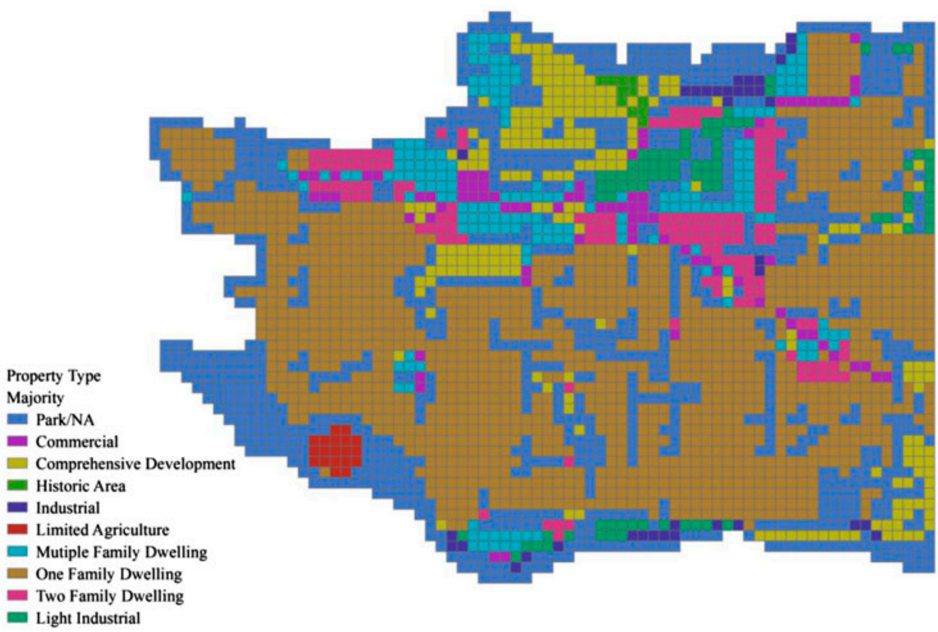

Figure 6. Vancouver's dominant property types by 200 m grid cell.

Table 1. The human and urban environmental covariates used in Model 1.

Data	Source	Description
Road Density	GeoBase National Road Network Version 2 (http://www.geobase.ca)	A collection of primary and secondary roadways at 1:100,000 scale resolution
Dominant property type	Vancouver City/Municipal Tax Information	Dominant property types per 200 m were calculated using a majority and geocoded property locations
Residential property count	Vancouver City/Municipal Tax Information	Property counts were calculated by selecting comprehensive, single and multiple family dwellings, then counting the frequency using a zonal statistic
Residential land value	Vancouver City/Municipal Tax Information	Property values were calculated by selecting comprehensive, single and multiple family dwellings, then averaging the land values using a zonal statistic
Commercial property count	Vancouver City/Municipal Tax Information	Property counts were calculated by selecting commercial dwellings, then counting the frequency using a zonal statistic
Commercial land value	Vancouver City/Municipal Tax Information	Commercial property values were calculated by selecting commercial dwellings, then averaging the land values using a zonal statistic
Number of streetlights	City of Vancouver Open Data Catalogue (http://data.vancouver.ca/datacatalogue/index.htm)	Coordinate locations of each pole across the city of Vancouver. Street poles were counted by 200 m grid cell
Ambient Population	LandScan (http://web.ornl.gov/sci/landscan/)	At 1 km resolution, created by disaggregated census population counts across spatial areas using spatial imagery and environmental characteristics to distinguish likely locations of population activity over 24 h
Graffiti rate per 1000 persons	City of Vancouver Open Data Catalogue (see above)	Weekly updated location of graffiti. We counted occurrence rate per 200 m grid and 1000 persons as a surrogate of socioeconomic status
Census population	2011 Canadian Household Census	Dissemination block counts were equally proportioned into the 200 m grid

parameters fit using a logit link function and maximum likelihood estimation) (Burns & Burns, 2008).

Model 2 used only observed crime data in the regression model. Prior to running models, we assessed variable importance (using a Knox ratio statistic) and assessed variable correlation to ensure models were statistically robust. Crime data were summarized both for general trends through all years, with more detailed patterns quantified from the past 240 days of data, which maximized detail while keeping computations manageable. Predictions were mapped and visually compared between observed and predicted spatial patterns to assess model accuracy.

Results

Summarizing patterns in observed BNEs

Exploratory analysis of observed data revealed distinct patterns in the characteristics of break and entry offences across Vancouver. Observing annual trends, we found a progressive decrease in the frequency of BNEs for both the residential and the commercial properties (see Figures 7(a)–(d) and 8(a)–(d)).

Residential BNEs decreased from 6224 recorded offences in 2001 to 3336 offences in 2012. Similarly, commercial offences decreased from 2535 offences in 2001 to 1692 offences in 2012. For both the residential and the commercial BNEs, there were no substantive month-to-month variations in the frequency of offences (see Figures 7(a)–(d) and 8(a)–(d)). There was a slight increase in the frequency of BNEs on Fridays for both residential and commercial break-ins though the proportional increase only rose by 1–2% over the other weekdays from 2001 to 2012. Contrasting the monthly and weekday temporal trends, we observed distinct differences in the occurrences of residential and commercial BNEs by hour. Residential offences substantially decreased between 1:00 and 6:00 when residents were most likely at home. Conversely, there were three peaks in the frequency of BNEs at 8:00, 12:00, and 18:00. All other times had a moderate frequency of occurrence (see Figure 7(a)–(d)). Commercial BNEs occurred most often during the 3:00, 4:00, 5:00, 17:00, and 18:00 intervals, while offences dramatically decreased during the daylight hours between 6:00 and 16:00. All other times exhibited a moderate frequency of offences (see Figure 8(a)–(d)).

Spatially, there was consistency in BNE locations from 2001 to 2012 (see Figure 9(a)–(d)).

The downtown northern portion of Vancouver had the majority of BNEs with sections of the West End, and Downtown surrounding neighborhoods of Strathcona, Kitsilano, Fairview, Mount Pleasant, and southcentral regions of Oakridge and Marpole suffering the highest intensity of property crime. Commercial property crimes exhibited linear spatial trends clustering around the 12th Avenue, Knight, and Kingsway highways (see Figure 9(b) and (d)).

Hot spots of commercial BNEs resided in the downtown neighborhood and sections of Fairview and Mount Pleasant neighborhoods that border downtown. There were indications of local hot spots in the southern Arbutus Ridge and Marpole areas; although

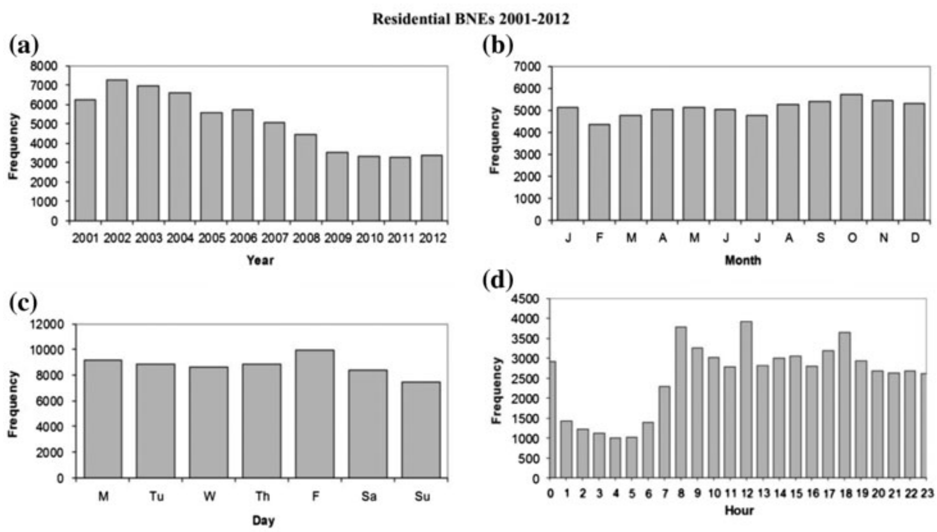

Figure 7. 2001–2012 temporal trends of Vancouver's residential BNEs.

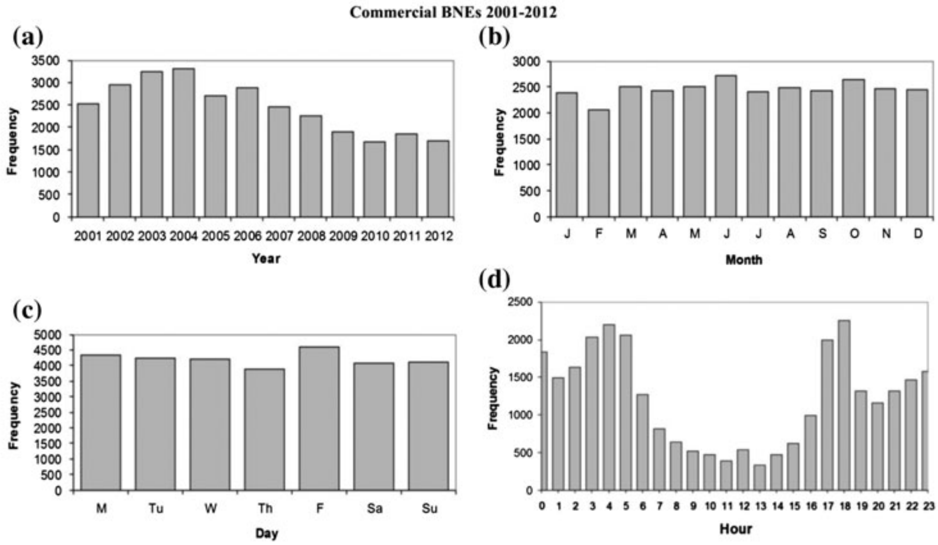

Figure 8. 2001–2012 temporal trends of Vancouver's commercial BNEs.

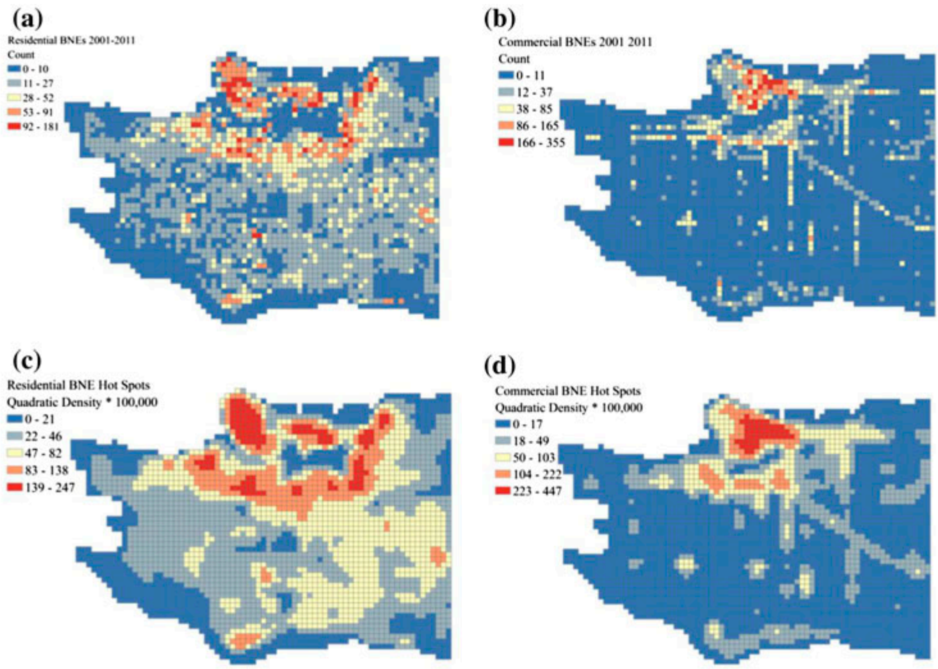

Figure 9. Vancouver's 2001–2011 break and entry patterns. Maps (a) and (b) depict the frequency of break-ins per 200 m grid and maps (c) and (d) display the smoothed intensity of break-ins from 2001 to 2011 for the residential and commercial properties, respectively.

the southern portion of Vancouver had fewer commercial break-ins likely because of the spatial arrangement of commercial properties (see Figure 5(b)).

Predicting future BNEs

Preliminary analysis indicated that residential break-ins had an increased likelihood of repeat and near repeat occurrences up to an 850 m radius and within hours to days of the last event. Within zero to one day after the initial occurrence, there was a 53% chance of reoccurrence up to 850 m from the originating event. Increased probabilities decayed rapidly with time. There was an increased probability at the seventh day after the originating event with the odds of a repeat offence within 850 m increasing by 24%. Commercial BNEs were closely related in time and space, and were influenced within one and two days after the original crime and 500 m away, with a 53 and 21% chance of increasing reoccurrence, respectively.

For Model 1 (residential), 11 data-sets were statistically significant predictors ($\alpha = .05$). The strongest predictor variables were the count of BNEs up within 850 m from the event in the last 24 h, 24–48 h, and seventh day. Proportion of historical crime by time and day was also significant, as was road density, dominant property type, count of residential crimes in each cell, ambient population, and residential property count. With Model 2 (residential), which was built on only crime data, the same crime variables were significant as in Model 1 (residential).

Model 1 (commercial), which was fit with covariate and crime data, had 14 statistically significant predictor variables ($\alpha = .05$). These included the count of BNEs up to 500 m away from the crime in the last 24 h and 48 h. Again, proportion of historical crime by time and day were strong predictors. Other reliable variables for prediction included road density, count of commercial crimes from 2001 to 2011 and commercial property count, density of commercial offences from 2001 to 2011, ambient population count, graffiti rate, census population count, commercial property value, and dominant property type. Consistent with Model 2 (residential), with the commercial version of Model 2, we observed that the same crime variables (crime in the last 24 h and 48 h) were significant. We have mapped relative probabilities of possible BNEs based on output of Models 1 and 2 (see Figure 10). These maps can be overlaid with observed data BNEs to evaluate the models.

Discussion

Our results contribute to the growing body of literature studying patterns in criminal offences. Following the results of Short et al. (2010) and Johnson et al. (2007), we found both residential and commercial crimes had a strong spatial clustering over short time periods suggesting a near-repeat offence dynamic, and over a longer time frame a core of break and entry offences (Sagovsky & Johnson, 2007; Townsley, Homel, & Chaseling, 2003). Our results indicated that perpetrators prefer to reoffend where they have local knowledge about residents' routine activities, possessions, and can confirm successful property entry (Wright & Decker, 1994). Recurrent BNEs, in both commercial and residential properties, were most likely to occur in the downtown and surrounding neighborhoods of Vancouver, which is likely the result of a greater population and property base.

Researchers have discussed the need to build crime forecasting capabilities that can be frequently updated (Haberman & Ratcliffe, 2012). Our results indicate that within

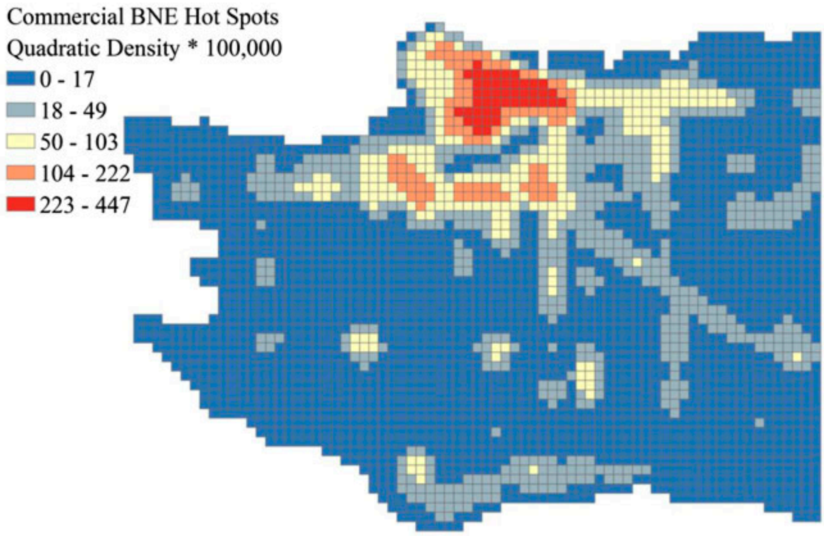

Figure 10. Example of a comparison of observed break-ins compared to probability of a break-in.

short periods of time and nearby distances of a break-in, there is a significant increase in the chance of another break-in. Therefore, we programmed an automated calculation of crime in the past hours or days from mapped data, available from most police dispatch systems, and in doing so have increased the functionality and speed of computation for identifying possible future crime locations. Further, by incorporating the most recent counts of the break-ins in the immediate locations with data on historical BNE patterns within the flexible modeling framework, we have provided a functioning and automated approach to updating prediction of break and entry odds every 4 h.

Overall, the predictive model was limited by the relatively rare occurrence, statistically speaking, of both residential and commercial BNEs. Considering that the police recorded 3336 residential break-ins and 1692 commercial break-ins in 2012, the odds of a break-in per grid cell were extremely low, .0005–.0002%, respectively, if every cell and time-interval was considered. The rarity of both the residential and commercial break-in compared to the 4-h modeling interval posed some modeling limitations. These limitations were largely a function of the temporal scale. Over a month to a year, there is a clear indication of break and entry clustering; however, when assessed multiple times per day, the pattern is more difficult to predict. For any crime event, the environmental characteristics and count of crimes in the last hours or days in adjacent cells may be identical, and in one circumstance a repeat break and entry occurs and in the other it does not. This 'randomness' leads to a reduced strength of the explanatory power of the covariates, especially in the case of the residential break-in model where BNEs have occurred in almost every grid cell over 2001–2011.

Studies have demonstrated that crime prevention strategies targeted to hot spots have led to substantial reductions in offences (Braga, 2001, 2005; Braga, Kennedy, & Bond, 2008; Weisburd et al., 2006). Models that incorporate both people and place characteristics, as well as crime data, may be suitable for mapping relative risk of BNEs. However, our preliminary investigations suggest that false positives, or indications of break and entry likelihood where none will occur, may be high. The emphasis of these models on the nature of the environment may be more appropriate for predicting crimes over broader time periods, such as monthly trends. Conversely, models built largely from the crimes occurring in the last 24 and 24–48 h pinpointed intersections of crime probability based on the spatial proximity to the last break and entry. These results can be used as flags of potential break and entry in subsequent hours and day. However, it can be difficult to predict these at fine spatial resolutions given the importance of spatial neighborhoods of 850 m for residential and 500 m for commercial crimes.

A unique aspect of our research is that the model we developed is statistical and based entirely on data. Other similar models have used mathematical approaches such as random walks (Jones, Brantingham, & Chayes, 2010; Short et al., 2009) to represent processes of crime. Given the fine detail of VPD's data and long-time series of available data, a statistical model can harness past information on crime to predict future patterns. However, our research suggests that using only crime data may limit the spatial and temporal resolution of the model. For instance, when only using the crime data, it will be difficult to generate a model at a finer spatial scale than 850 m for residential properties and 500 m for commercial properties. These areas are too large to be feasible for tasking police patrol units. By including data on the urban and human context, the finer grid cells model is useful, but initial investigations indicate the temporal pattern of crime predicted may be more appropriate for representing monthly patterns.

Our model predicted BNEs six times per day. The time periods were limited by the size of the data-sets, the accuracy of event time recorded in the crime data, and the frequency with which a system for implementation would update data. When structured for a model that predicted six times per day, the observed data were stored in over 6 million cells. One hour models would require close to 150 million cells, making computational limitations a serious problem. As well, the success of the model would be limited by variation in when the crime occurred relative to when the crime was reported, which is difficult to correct to within an hour time frame. In an operational context, the frequency of predictive mapping, which is based on the temporal detail of data, will always be limited to the frequency in which new data are added to the system. As such, our recommendation is that future researchers should consider approaches that integrate statistically or data-based methods with mathematical approaches for modeling known processes of crime. Harnessing the power of growing data-sets with knowledge of criminal patterns may allow us to customize model parameterization, while mathematical approaches will enable more detailed space and time predictions.

The maps provided are appropriate for relative risk assessment of the likelihood of BNEs (e.g. Caplan, Kennedy, & Miller, 2011). In order to assess how well the models are predicting crime, a method for converting likelihood into expected crime is needed. The standard approach would be to threshold the likelihood surface and above a threshold to classify the crime as predicted. The predicted crime can then be compared to observed testing data to determine the accuracy and number of false positives. Given the low probability of any crime occurring, it is unclear how to set the threshold for identifying a predicted crime event. If the value is too high, there will be an overwhelming number of false predictions. However, setting the threshold too low may lead to the model missing most of the real crime. There may be benefit to considering spatial or temporal pattern information in setting the threshold. For instance, given that all crime is unlikely, it may be when there is a large change in the predicted value for a specific grid cell that the potential for crime should be highlighted. Further research is required before the model can be fully assessed or implemented.

An important component of implementation is the automation of the predictive system. Modeling BNE risk multiple times per day is only feasible if it can be performed without analyst intervention, particularly when predictions are required outside typical working hours. Ideally, this model will be automated through integration within mobile GIS-style systems. For instance, systems are being developed to outfit police vehicles with GIS mapping that provides insight into historical trends and recent changes in activity. Such systems are the ideal platform for integrating automated predictive mapping capabilities that are designed for allocating patrol resources.

Conclusion

Intelligence-led policing is supported by spatially explicit models for predicting where and when future crimes will occur. Our models predicted future BNEs for residential and commercial locations based on detailed data collected by the VPD on where and when observed crimes occur. Models predicted BNE locations six times per day and the models are designed to be implemented in a mobile GIS system that will allow for automated updating. We have generated models based on both crime and urban and human environmental data, as well as on only crime data. When models considered the environmental context, the predictions had great spatial detail (200 m by 200 m), but the patterns seem to be most representative of long-term trends. When only crime data were used in predictions, the patterns were representative of short time periods, but the spatial detail of maps is lower (500–850 m). For patrol purposes, finer spatial and temporal resolutions are required. The next phase of models should integrate statistical data-based models, such as we have presented here, with mechanistic models that base predictions on mathematically represented knowledge of typical crime patterns. An integrated modeling approach will allow the powerful crime data to be leveraged in a dynamic framework. As well, the model needs to be further evaluated by converting crime likelihood maps into maps of predicted crime and comparing the model results with observed data. Model validation will require thoughtful consideration of how to threshold likelihood surfaces to predict crime events.

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Notes on contributors

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