Computers, Environment and Urban Systems 66 (2017) 83–95

Contents lists available at ScienceDirect

Computers, Environment and Urban Systems

journal homepage: www.elsevier.com/locate/ceus

Built environment and violent crime: An environmental audit approach using Google Street View

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ARTICLE INFO

Article history:
Received 1 July 2016
Received in revised form 4 July 2017
Accepted 6 August 2017
Available online 17 August 2017

Keywords:
Built environment
Violent crime
Spatial filtering
Environmental audit
Google Street View

ABSTRACT

Recent studies empirically support the role of the built environment in inducing or hindering violent crime. Particularly, studies of the broken window theory have provided evidence that physical disorder is an environmental correlate of crime. This includes broken windows, vacant/abandoned housings, abandoned cars on street, graffiti, and decayed street lighting, among other things. Current studies are limited by the difficulty involved in collecting fine-scale quantitative environmental data. The conventional environmental audit approach, which aims to assess environmental features, is costly, time-consuming, and burdensome. In this study, we use Google Street View to study the relationship between violent crime and physical features of urban residential environment. More concretely, a Poisson regression model with spatial filtering is used to identify socio-economic correlates of violent crime. Parting from the hypothesis that omission of built environmental factors results in systematic residual pattern, we proceed to analyze the spatial filter to select sites for virtual environmental audits. A series of physical environmental factors are identified using contingency table analysis. The results provide both theoretical and practical implications for several theories of crime and crime prevention efforts.

1. Introduction

Social disorganization theory has consistently demonstrated the relationship between social disorder and violent crime. Accordingly, numerous studies argue that physical signs of neighborhood disorder can impact violent crime (Anderson, MacDonald, Bluthenthal, & Ashwood, 2012). The important role of micro-level physical characteristics of built environment in inducing and deterring violent crime has been confirmed in several studies (Brantingham & Brantingham, 1993; Groff, Weisburd, & Morris, 2009; Sampson & Raudenbush, 2004). This is intuitive: physical features of neighborhood environment are an integral part of neighborhood ecology (Greenberg & Schneider, 1994), and in this sense, obvious signs of physical decay tend to indicate an absence of informal social control and collective efficacy in the neighborhood (Sampson, Raudenbush, & Earls, 1997). This, in turn, can lead to disproportionate concentration of violent crimes. While researchers have become increasingly interested in these complex mechanisms of social-environmental interaction (Malleson & Birkin, 2012), their understanding have been limited by the lack of fine-scale quantitative data of the built environment.

Environmental audits are a direct way of developing inventories of the features of the built environment (Moniruzzaman & Páez, 2012a). Environmental audit tools for physical activities (e.g., walking, cycling) and neighborhood safety have undergone extensive development and testing over the past several decades (e.g., Clifton, Smith, & Rodriguez, 2007; Day, Boarnet, Alfonzo, & Forsyth, 2006; Hoehner, Ivy, Brennan Ramirez, Handy, & Brownson, 2007; Moniruzzaman & Páez, 2016; Perkins, Meeks, & Taylor, 1992). These inventories have been more successful in helping to decide "what" to audit. However, questions of "where" and "how" to audit remain under-investigated. In other words, current literature fails to address appropriate selection of target sites and effective data collection method. First, sites are conventionally selected through sampling (e.g., McMillan, Cubbin, Parmenter, Medina, & Lee, 2010; Perkins, Wandersman, Rich, & Taylor, 1993). While convenient, this approach fails to account and control for underlying effects of socio-economic correlates – which may result in misleading conclusions (Moniruzzaman & Páez, 2012a). Environmental audits, therefore, should be conducted at target sites most likely to yield novel information. Second, most conventional environmental audits involve on-site observations (Edwards et al., 2013). Auditors have to visit sites and directly collect environmental data. This approach is costly, time-consuming, and burdensome, especially for large-scale studies and dispersed

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http://dx.doi.org/10.1016/j.compenvurbsys.2017.08.001
0198-9715/

distribution of study sites. Effective tools to enable quick and systematic collection of environmental characteristics associated with violent crime remain under-investigated.

Technology advancements provide new tools to explore geographical landscapes (Chen, Lin, Hu, He, & Zhang, 2013; Clarke, Ailshire, Melendez, Bader, & Morenoff, 2010; He et al., 2013). Google Street View (GSV), for instance, has recently been used as a tool to investigate urban environment (Salesses, Schechtner, & Hidalgo, 2013). It has been successful in helping to virtually and remotely audit environmental features associated to public health issues and physical activities (Clarke et al., 2010; Edwards et al., 2013). The results of existing research confirm the reliability of this approach for all but the most ephemeral attributes of the environment even over a period of years (Clarke et al., 2010). While much research has been devoted to walkability, for instance, to date little attention has been given to the use of these technologies to identify environmental features associated with violent crime.

In this paper, we illustrate how GSV can be used to study the relationship between violent crime and physical characteristics of urban residential blocks. Specifically, we explore two questions: "where" the audit needs to be conducted, and "how" to effectively audit by considering the purpose and cost. This study contributes to the literature in the following ways. First, we address the question of "where" to audit by using Poisson regression model with spatial filtering (Griffith, 2002). After controlling for relevant socio-economic correlates, target sites can be determined by analyzing residual spatial pattern as retrieved by a spatial filter (see Moniruzzaman & Páez, 2012a). Second, we use GSV to systematically identify physical features associated to violent crime, after socio-economic correlates have been controlled for in the model. This procedure is fairly general, and can be applied to other cases where on-site audits are challenging or unfeasible. Third, we develop a desktop data collection tool to facilitate virtual audit data collection. With some modification, the tool can be retooled for multi-purpose environmental audits. Fourth, this study provides an alternative way to re-evaluate influential theories of crime. Results obtained from the Poisson estimation and GSV-based environmental audit give credence to social disorganization theory, routine activity theory, and broken window theory. This can help to provide practical insights for Crime Prevention Through Environmental Design (CPTED) initiatives and inform focused crime prevention efforts.

The remainder of the paper is organized as follows. In Section 2, we summarize previous studies on the relationship between physical features of the built environment and violent crime. We also discuss current methods used for environmental audit. In Section 3, we discuss the modeling techniques, development of desktop data collection tool, and GSV-based audit procedure. In Section 4, we provide the results of Poisson model estimation, audit site selection, and analysis of contingency tables. In Section 5, we discuss the theoretical and practical implications of the study. The paper then concludes with a discussion of contributions, future directions, and limitations of the present study.

2. Background

The literature on spatial analysis of violent crime provides evidence that both the social and built environmental context can induce or inhibit violent crime (Sampson & Groves, 1989; Sampson & Raudenbush, 2004; Spicer, Reid, Ginther, Seifi, & Dabbaghian, 2012). Of interest are various types of fine-scale physical characteristics of built environments. In this section, a brief review of primary criminological theories and empirical evidence underpinning this study is presented, followed by a summary of current environmental audit approaches.

2.1. Social disorganization, routine activity, and violent crime

Social disorganization theory (SDT) (Sampson & Groves, 1989) and routine activity theory (RAT) (Cohen & Felson, 1979) are two ruling spatial theories of crime that have been widely employed to understand crime from social ecology and neighborhood characteristics.

Social disorganization is defined as "the inability of local communities to realize the common values of their residents" (Bursik, 1988, p. 521). It explains crimes from general characteristics of social structure and social control on which offenders and victims are embedded. Four elements are used to explain criminal activity: socio-economic deprivation (SED), residential mobility (RM), family disruption (FD), and ethnic heterogeneity (EH).

RAT suggests that crimes occur at the intersection of motivated offenders, suitable targets, and the absence of capable guardians. It focuses on the role of "places" (Eck & Weisburd, 1995) in inhibiting or encouraging crimes. RAT uses three elements to understand crime: motivated offender (MO), suitable target (ST), and guardianship. Recent evidences prove that neighborhood level variables can be used to capture the potential of criminal victimization by measuring the elements of RAT (Andresen, 2006a, 2006b). Researchers suggest that an integration of SDT and RAT can provide robust theoretical explanation for spatial studies of crime. This lays foundation for the selection of independent variables in this study.

2.2. Physical features of built environment and violent crime

The primary criminological theories underlying current empirical studies of environmental correlates of crime are broken windows theory (BWT) (Wilson & Kelling, 1982), crime prevention through environmental design (CPTED) (Jeffery, 1971), and situational crime prevention (SCP) (Clarke, 1995).

The BWT argues that visible evidence of physical disorder, such as broken windows, vacant/abandoned properties and abandoned cars on the street, are not only evidence of possible criminal activity, but can also facilitate further crime and other deviant behaviors (Wilson & Kelling, 1982). This link has previously been discussed in the work of Jacobs (1961), who emphasized the important role of pedestrian traffic, visual signs of environmental disorder, and social interaction between residents. The BWT literature emphasizes the importance of well-kept property to keep it from falling into disarray.

Consistent with BWT, literature on CPTED argues that crime and fear of crime can be inhibited though proper design and modification of physical features of residential environment (Crowe, 2000). Seven key elements are suggested to create "defensible spaces" and reduce crime opportunities (see inter alia Marzbali, Abdullah, Razak, & Tilaki, 2012; Cozens & Love, 2015). These are 1) territorial reinforcement (e.g., fences, property signs, etc.); 2) surveillance; 3) access control; 4) activity support (e.g., legitimate activities in parks); 5) image/maintenance (e.g., graffiti and litter); 6) target hardening (e.g., locks, alarms); and 7) geographical juxtaposition (i.e., surrounding land uses, such as schools or bars). Similar to CPTED, SCP also suggests that crime opportunities can be reduced through environmental modification, but with a focus on certain types of crime and involving the use of technologies and procedures (Cornish & Clarke, 2003). A growing body of research provides evidence that various types of violent crime can be controlled through CPTED and SCP strategies. An extended review of these concepts can be found in Cozens and Love (2015).

Empirical studies give credence to the above theories by evaluating the effects of various aspects of physical environment on violent crime, such as vegetation (Wolfe & Mennis, 2012), street lighting (Steinbach et al., 2015), graffiti and litter (Loukaitou-Sideris, Liggett, Iseki, & Thurlow, 2001), vacant and abandoned properties (Hannon, 2005), abandoned cars (Braga & Bond, 2008), and block watch signs (Donovan & Prestemon, 2012), among many other features related to the design of residential and non-residential property (Marzbali et al., 2012). Theoretical foundations and empirical evidences of these physical features are summarized in Table 3.

These findings are rooted in both theoretical and practical development of criminological frameworks, such as BWT, CPTED and SCP. Like all theories, these are enriched by empirical studies and continue to evolve as new evidence emerges. For example, some studies on BWT found little evidence for the effectiveness of policing practices in reducing crime (e.g., Harcourt & Ludwig, 2006). Some studies on CPTED have found contradictions between territoriality and surveillance (e.g., Reynald, 2009). Territoriality is enhanced by high fences due to their ability to keep people out of the property, whereas surveillance may be hampered by the presence of fences. However, as Cozens and Love (2015) suggested, future practices need to absorb emerging evidence and theories from environmental criminology to further assess the effectiveness of CPTED.

Our review of the literature on the relationship between physical environment and violent crime provides some insights.

Firstly, many argue that both physical disorder and violent crime can be affected by concentrated socio-economic disadvantage, therefore, the link may be blurred in the absence of controls for poverty and collective efficacy (Gau & Pratt, 2010; Sampson & Raudenbush, 2004). Furthermore, the effects of physical features may be conditional on socio-economic conditions, such as variation of population mobility (Wilcox, Quisenberry, Cabrera, & Jones, 2004) and disadvantage index (Stucky & Ottensmann, 2009). Therefore, to more effectively measure the effect of the physical environment, social structural conditions need to be controlled by means of a wide array of social disorganization variables and routine activity variables. This is something we achieve in our approach by using a statistical approach to controlling for a wide array of covariates before selecting sites for environmental audits. In this way the effects of physical disorder can be explored in a more systematic way.

And secondly, the above theories are influential but as noted they remain the subject of debate. Studies of the rigorous influence of BWT and CPTED have remained speculative, due in part to the difficulty in data collection of fine-scale physical features. Conventional data collection practices provide valuable methods, but are limited by the involvement of burdensome field work and cost. The approach illustrated in this study allows for cost-effective systematic collection of environmental data associated with violent crime.

2.3. Environmental audit approach

Environmental audits represent a direct and practical way to assess physical features of environment associated with physical activity and safety. Numerous audit instruments have been developed, such as the Pedestrian Environment Data Scan (PEDS) (Clifton et al., 2007), the Revised Block Environmental Inventory (RBEI) (Perkins et al., 1992), the Irvine-Minnesota Inventory (IMI) (Day et al., 2006), the University of Maryland Urban Design Tool (Ewing, Handy, Brownson, Clemente, & Winston, 2006), the Analytic Audit Tool (Hoehner et al., 2007), the Systematic Pedestrian and Cycling Environmental Scan (SPACES) (Pikora et al., 2002), the Public Open Space Desktop Auditing Tool (POSDAT) (Edwards et al., 2013), and several manuals for CPTED (ODPM/Home Office, 2004).

Despite the widespread availability of these instruments, fine-scale environmental data are not typically collected in a systematic way (Parmenter, McMillan, Cubbin, & Lee, 2008). Conventional audit practices require environmental features to be collected through on-site observation. Trained auditors have to walk or drive through the audit sites, record environmental data through filling out paper checklist (Clifton et al., 2007), filling digital checklist on handheld device (Moniruzzaman & Páez, 2012a), videotaping (Cohen et al., 2000), on-site photographing (Austin & Sanders, 2007), or using GPS-enabled geospatial video (Mills, Curtis, Kennedy, Kennedy, & Edwards, 2010) and/or GPS-enabled passive photographing (Oliver et al., 2013). The need to deploy research personnel on site makes audits time-consuming, costly, burdensome, and potentially risky.

Fortunately, the growth of geospatial technologies now provides increased opportunities to remotely and virtually observe and characterize geographical landscapes. Google Street View (GSV), for instance, has recently been utilized to investigate urban built environments (Clarke et al., 2010; Edwards et al., 2013; Silva, Grande, Rech, & Peccin, 2015). A growing body of studies identifies GSV as a valuable and reliable data collection tool for the assessment of environmental correlates of physical activities such as walking (Griew et al., 2013), cycling (Vanwolleghem, Van Dyck, Ducheyne, De Bourdeaudhuij, & Cardon, 2014), health issues such as children's healthy behavior (Odgers, Caspi, Bates, Sampson, & Moffitt, 2012) and elder's wellbeing (Burton, Mitchell, & Stride, 2011). It has been suggested that GSV should be used with caution, due to the temporal instability of date stamps (month and year) and absence of time information (day) (Curtis, Curtis, Mapes, Szell, & Cinderich, 2013; Salesses et al., 2013). However, previous studies generally report accurate and consistent agreements between field audit and GSV-based virtual audit, and dramatic savings of up to 90% of audit time (e.g., Clarke et al., 2010; Edwards et al., 2013). This is particularly true for relatively large, visible features of the environment (Badland, Opit, Witten, Kearns, & Mavoa, 2010; Ben-Joseph, Lee, Cromley, Laden, & Troped, 2013; Kelly, Wilson, Baker, Miller, & Schootman, 2013; Odgers et al., 2012; Rundle, Bader, Richards, Neckerman, & Teitler, 2011).

Although this novel tool has been increasingly employed, it has rarely been utilized to identify physical features associated with violent crime. Salesses et al. (2013) studied the link between urban environment and perception of safety using GSV imagery. Their study provides empirical test of GSV methods, but does not follow a systematic site selection procedure. This is a point that our approach addresses.

3. Data and methods

A systematic method to measure the effect of physical environment on violent crime is used. At the foundation of our approach are statistics of violent crime and a wide array of social disorganization variables and routine activity variables. These variables are examined using a Poisson regression model estimated at block group (BG) level. After controlling for social structural conditions, we hypothesize that the residual spatial pattern is attributable to the absence of physical environmental variables (one source of spatial autocorrelation being omitted relevant variables; McMillen, 2003). To retrieve the spatial residual pattern, we use eigenvector-based spatial filtering when estimating the Poisson model (Griffith, 2002). Selection of sites for environmental audits is based on analysis of the residual pattern, if any. Finally, these candidate sites are audited using GSV. In this section, we describe the technical aspects of this approach.

3.1. Crime data and census data

Violent crime data was obtained from the Columbus Division of Police. The dataset provides a series of spatial and temporal attributes, such as time, date, location and type of crime incidents. Four types of criminal offenses are classified as violent crime by the FBI: murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. The period covered by the dataset is from 1998 to 2002.

Previous studies have suggested that crime data does not necessarily need to be averaged if the relationships between socio-economic indicators and multi-year crimes are significantly stable (He, Páez, Liu, & Jiang, 2015). We use violent crime of 2002 in the present study for two reasons. First, there is a stable temporal relationship in Columbus between violent crime and social structural correlates of crime (He et al., 2015). Second, the use of 2002 data minimizes the gap between crime data and street view imagery (i.e., 2007).

The dataset records 4791 violent crimes in 2002. The geocoding success rate of crime points is 95.0%. The distribution of violent crime of 2002 in Columbus is shown is Table 1. The variable is skewed to the right, with a range from 0 to 67 and mean value of 8.61. According to MacDonald and Lattimore (2010), this suggests that a Poisson distribution may appropriately fit these data.

Data from the US Census 2000 was used to generate socio-economic and demographic independent variables. The Census data is mainly collected from the Summary File 3 (SF3) from the US Census Bureau.

Table 1
Descriptive statistics for variables used in the regression analysis (567 observations).

Variable	Mean	S.D.	Min	Max
Dependent variable				
Count of violent crime in 2002	8.61	9.74	0.00	67.00
Socio-economic deprivation				
% of population below the poverty level	18.52	15.91	0.00	76.81
% of population with bachelor's degree	15.91	12.77	0.00	52.04
% of unemployed population	3.99	3.42	0.00	30.77
Ethnic heterogeneity				
Heterogeneity index	0.33	0.16	0.00	0.76
% of foreign-born population	6.09	8.40	0.00	95.86
Residential mobility				
% of renter-occupied housing units (*suitable targets*)	49.77	28.81	0.00	100.00
% of population living in the same house as 5 years ago	46.01	19.21	0.00	100.00
Family disruption				
# of single-parent families	53.51	48.20	0.00	397.00
Guardianship				
population density (in thousands)	2.69	1.99	0.02	14.90
% of vacant housing units	8.22	6.65	0.00	46.00
Motivated offenders				
# of young male population age 15–24 (log transformed)	4.13	1.21	−11.51	7.70

Furthermore, supplementary data were obtained from the National Historical Geographic Information System (Minnesota Population Center, 2011). Independent variables were selected based on our review of social disorganization theory (SDT) (Sampson & Groves, 1989) and routine activity theory (RAT) (Cohen & Felson, 1979) as described next.

Informed by extensive empirical literature (e.g., Naffine & Gale, 1989; Andresen, 2006a, 2006b; Chun, 2014; He et al., 2015; He, Páez, & Liu, 2016), independent variables are selected to measure four elements of SDT. We use poverty rate, percent of educated population, and unemployment rate to capture SED. RM is captured by percent of rental residences and locational stability (represented by population living in the same house as 5 years ago). FD is captured by number of single-parent families. EH is captured by immigrant concentration (represented by percent of foreign-born population) and Heterogeneity Index. The index is defined as $1-\sum p_i^2$ (Sampson & Groves, 1989), where i denotes the number of racial group, and p_i is the percent of population within a given group. Racial groups in this study include: White; Black; American Indian, Eskimo, or Aleut; Asian or Pacific Islander; and other races. The index ranges from zero to one. A value of zero indicates maximum homogeneity, and one indicates maximum heterogeneity.

In terms of three elements of RAT, informed by Andresen (2006a), we use number of young male population to capture MO. ST is captured by percent of rental residences. Guardianship is captured by population density and percent of vacant properties. Table 1 provides descriptive statistics for all variables used in the regression analysis. The collinearity test for all SDT and RAT variables is shown in Table 2 in the Appendix, which does not identify pair-wise correlation in excess of 0.8 or −0.8, a common threshold as suggested by Andresen (2006a).

A positive relationship with crime is expected for poverty rate, unemployment rate, rental residences, single-parent families, Heterogeneity Index, vacant properties, and young male population. A negative relationship, on the other hand, is expected for educated population, locational stability, immigrant concentration, and population density.

3.2. Poisson regression with eigenvector-based spatial filtering

The decision of "where" to audit is based on the use of Poisson regression with eigenvector-based spatial filtering (Griffith, 2002). The model is used to estimate the relationship between count of violent crime and a series of social disorganization and routine activity variables at BG level.

The use of Poisson regression in violent crime analysis is reviewed by MacDonald and Lattimore (2010). The unimodal and skewed nature of Poisson distribution makes Poisson regression more appropriate to model (typically skewed) crime counts. In order to better capture spatial autocorrelation and produce model estimates that are not affected by spatial autocorrelation, recent studies incorporate eigenvector-based spatial filtering (Chun, 2014; Griffith, 2002; Moniruzzaman & Páez, 2012a). As a nonparametric approach, it is developed to transform spatially autocorrelated residuals into spatially independent residuals by transferring the embedded residual pattern to the mean of the model. The model thus incorporates a filtered variable that yields clean residuals.

Spatial filtering uses a judiciously selected set of eigenvectors obtained from a transformed spatial weight matrix, which takes the following form:

$$\left(I-11^T/n\right)C\left(I-11^T/n\right) \tag{1}$$

where I denotes an identity matrix, 1 denotes a column vector of ones, T denotes the matrix transpose operator, n is the number of spatial units, and C denotes an n-by-n spatial weight matrix.

Eigenvectors are orthogonal and uncorrelated, and represent n distinct map patterns. Each pattern represents a distinctive degree of spatial autocorrelation. The initial eigenvector E_1 indicates the map pattern which has the highest degree of positive spatial autocorrelation achievable given the spatial configuration of C. E_1 is followed by $E_2, E_3, \ldots, E_n$ in an decreasing order of the degree of spatial autocorrelation, where E_n indicates the highest possible degree of negative spatial autocorrelation (Moniruzzaman & Páez, 2012a). A combination of eigenvectors can describe systematic spatial patterns and act as proxies for relevant but omitted variables in the specification of Poisson regression model. Therefore, they can help to identify spatial autocorrelation from the

Table 2
Correlations for independent variables.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}
X_1	1										
X_2	−0.1758	1									
X_3	0.3791	−0.3066	1								
X_4	0.1827	−0.1701	0.1769	1							
X_5	0.1518	0.2506	−0.0594	0.3757	1						
X_6	0.5951	0.1348	0.2694	0.3564	0.3696	1					
X_7	−0.4095	−0.3347	−0.1642	−0.3202	−0.4441	−0.7903	1				
X_8	0.1628	−0.3492	0.3028	0.3052	0.0322	0.1972	−0.1301	1			
X_9	0.4964	0.1150	0.1008	0.0785	0.1366	0.4571	−0.4459	−0.0313	1		
X_{10}	0.2349	0.1199	0.0001	0.2421	0.1822	0.3666	−0.4521	0.2508	0.3336	1	
X_{11}	0.4478	−0.3024	0.4185	0.1402	−0.1199	0.3762	−0.1771	0.2212	0.0491	−0.0072	1

Note: X_1: poverty rate; X_2: percent of educated population; X_3: unemployment rate; X_4: Heterogeneity Index; X_5: immigrant concentration; X_6: rental residences; X_7: population living in the same house as 5 years ago; X_8: number of single-parent families; X_9: population density; X_{10}: number of young male population (log transformed); X_{11}: percent of vacant properties.

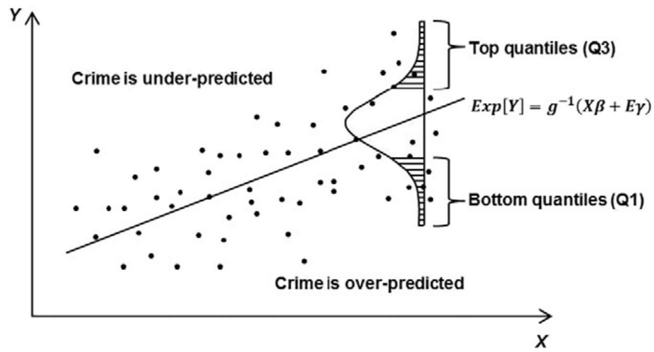

Fig. 1. Diagram of the use of bottom and top quantiles for audit site selection.

unexplained parts of dependent variable (Chun, 2014). A Poisson regression with eigenvector-based spatial filtering can be written in a following form (see Chun, 2014):

$$\mathrm{Exp}[Y] = g^{-1}(X\beta + E\gamma) \tag{2}$$

where Y denotes the dependent variable which follows a Poisson distribution, Exp[Y] denotes the calculus of expectation operator, g denotes a link function (logarithm in most cases), X denotes a vector of linear independent variables, β is a vector of regression coefficients, E denotes the spatial filter (which is a linear combination of selected eigenvectors), and γ denotes a parameter associated with the spatial filter. An assumption of Poisson regression is that the conditional mean equals to variance. To minimize the bias of over-dispersion, the intervals of confidence can be corrected by including an estimation of dispersion parameter for the Poisson distribution (Moniruzzaman & Páez, 2012b).

The filtered spatially auto-correlated parts from model residuals provide information of systematic over- and under-estimation of the dependent variable. In other words, the filter identifies the locations where the behavior (i.e., violent crime) is more common than expected after controlling for the covariates (i.e., those where the model under-estimates crime), and locations where crime is less common than expected (i.e., those where the model over-estimates crime). After controlling for socio-economic correlates (and possibly meso-scale environmental factors), we hypothesize that systematic over- and under-estimation are caused by the omission of finer-scale physical features of built environment that may encourage or hinder violent crime in a similar systematic way.

3.3. Audit site selection

Audit sites are selected based on the spatial filter in the following manner. The spatial filter is divided into three Quantiles, Quantile 1 (Q1) for the bottom third of observations (negative values), Quantile 2 (Q2) for the middle third (around zero), and Quantile 3 (Q3) for the top third (positive values). Next, as shown in Fig. 1, we select sites from BGs where crime counts are over-estimated (i.e., from Q1); further, we select sites from BGs where crime counts are under-estimated (i.e., from Q3). We hypothesize that: (1) in block groups where crimes are over-predicted (Q1) more built environment factors will be found that hinder crime; and (2) in block groups where crimes are under-predicted (Q3) more built environment factors that facilitate crime will be found.

During the process of selecting BGs we heed the suggestion that, in the manner of control-case studies, paired observations at similar levels of crime count from two groups should be selected (Moniruzzaman & Páez, 2012a). In other words, when one BG is selected from over-estimation group, the other BG having similar value of crime count shall be selected from under-estimation group. As shown in Fig. 1, those paired observations include wide-ranging values from both groups. The size of selection should meet the demand of sample size for further statistical analysis (in the present case, contingency table analysis). And the distribution of selected sites should be as random as possible across the study area.

3.4. Environmental audit using Google Street View

Google Street View (GSV) is a technology featured in Google Maps and Google Earth (Google Inc., 2016). Launched on May 25, 2007, it provides 360° panoramic street-level images which covering 39 countries and about 3000 cities. The GSV images were taken from positions along streets, and from a height of approximately 2.5 m and at about 10 or 20 m intervals. It allows users to virtually walk down streetscapes, and to navigate forward and backward, pan 360°, vertically rotate 290°, and zoom in/out.

To facilitate the virtual audit and data collection, a desktop audit tool was developed using ArcGIS Engine 10.0 (ESRI Inc., 2016) and Visual Studio 2008 (Microsoft Inc., 2016). The tool was developed based on the revised block environmental inventory (RBEI) designed by Perkins et al. (1992) to measure the physical environment of urban residential blocks. Shapefile data can be imported into the tool; environmental factors can be input using popup input windows, and can be saved as attribute data of corresponding polygon. Fig. 2 shows the interfaces of the data collection tool.

The RBEI measures three types of environmental features that have been associated with violent crime: physical incivility, territorial functioning, and defensible space (Perkins et al., 1992). First, it has been suggested that physical incivility (e.g., property damage and abandoned buildings) can influence residents' fear of crime or perception of safety. Second, territorial functioning features (e.g., yard decoration) reflect pride of ownership and territoriality. They have been linked to increased

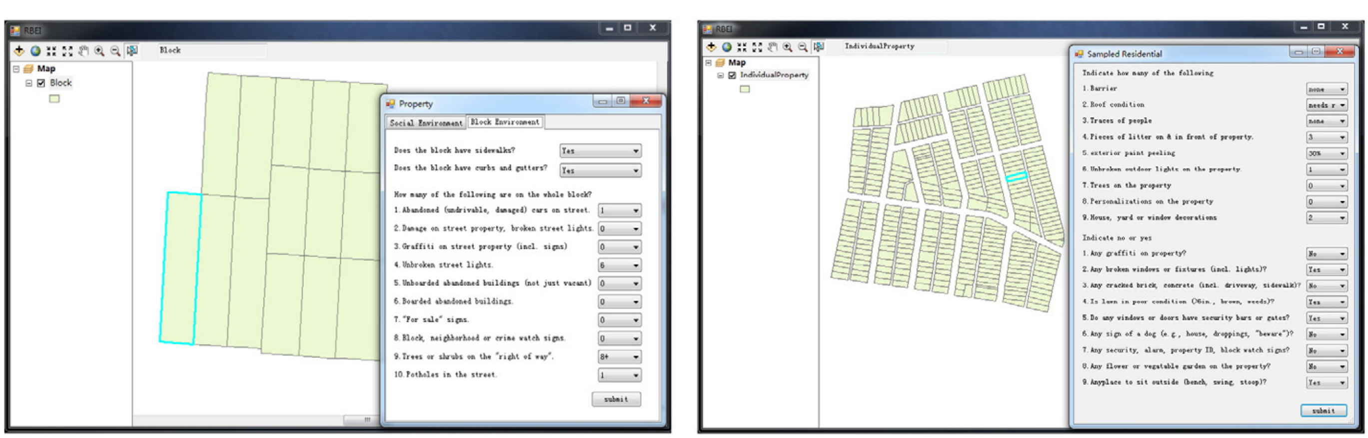

Fig. 2. The interface of RBEI tool for block level (left) and individual property level (right) data collection.

social interaction and sense of community. Third, the defensible space features can not only encourage territorial pride, but also physically hinder the commission of crime. For example, the presence of a fence can reflect both pride of territoriality as well as provide a physical barrier. Each type of environmental feature can be measured by a number of factors; the RBEI requires some of the factors to be audited at block level, and other more factors to be audited at individual property level. Informed by the RBEI checklist, three types of features are measured by 21 environmental factors at either block level or individual residential property level. For the block level factors, we audit the entire blocks, while for the individual property level factors, the RBEI requires at least eight properties of one block be audited. The list of 21 factors is shown in Table 3, along with the corresponding theoretical and empirical foundations.

Table 3
RBEI environmental factors (21) and corresponding theoretical and empirical foundations.

Factors	Theoretical/empirical foundations	Measure
Physical incivility		
Graffiti	Graffiti can be vandalism and has been positively associated with concentration of violent crime (Austin & Sanders, 2007; Shobe & Banis, 2014). The presence of graffiti could produce disorder, chaos, fear in neighborhoods, and indicates that crime is left unchecked (Doran & Lees, 2005).	Audited as continuous numeric responses and categorized as absent or present.
Damage on street property	Property damage and disrepair can influence residents' fear of crime or perception of safety (Perkins et al., 1992; Skogan, 1990).	Audited as continuous numeric responses and categorized as absent or present.
Potholes in the street	Physical signs of environmental decay can induce potential deviant behaviors and crime (Wilson & Kelling, 1982).	Audited as continuous numeric responses and categorized as absent/few (potholes ≤ 2) or some/dense (potholes > 2).
Unsecured abandoned buildings; Secured abandoned buildings	Abandoned buildings are associated with residents' fear of crime or perception of safety (Hannon, 2005; Perkins et al., 1992).	Audited as continuous numeric responses and categorized as absent or present.
Abandoned cars	Visible evidence of physical disorder, such as abandoned cars on the street, are evidence of possible criminal activity, and can facilitate further deviant behaviors and crime (Braga & Bond, 2008; Wilson & Kelling, 1982).	Audited as continuous numeric responses and categorized as absent or present.
Litter; Dilapidated exterior; Roof condition; Cracked brick or concrete	A decayed physical environment (litter, disrepair, graffiti, abandoned buildings, unkempt lots) conveys at least two messages: 1) the physical environment of neighborhood is neglected; and/or 2) informal and formal social control for deviant behavior has broken down (Cohen et al., 2000). Therefore, physical incivilities lead to increased crime and resident fear (Skogan, 1990; Wilson & Kelling, 1982).	Litter and dilapidated exterior were audited as continuous numeric responses and categorized as absent/few (number of litter ≤ 2; percentage of peeling ≤ 10%) or some/dense (number of litter > 2; percentage of peeling > 10%). Roof condition was originally audited as categorical responses: new roof, average roof, or roof needs repair. Cracked brick were originally audited as categorical responses: absent or present.
Broken windows or fixtures	Broken windows left unrepaired indicate that social control is weak in a neighborhood, which in turn imply that potential criminals are more likely to act (Loukaitou-Sideris et al., 2001). They are not only evidence of possible criminal activity, but can also facilitate crime and deviant behaviors (Braga & Bond, 2008; Wilson & Kelling, 1982).	Audited as continuous numeric responses and categorized as absent or present.
Territorial functioning		
Block or crime watch signs	Block watch signs can increase the probability of a criminal being observed, therefore, can be linked to decreased crime (Donovan & Prestemon, 2012).	Audited as continuous numeric responses and categorized as absent or present.
Trees or shrubs	The effects are mixed and depend on the type of vegetation. Small and view-obstructing trees are associated with increased crime, as they can provide cover to potential criminals (Donovan & Prestemon, 2012; Kuo, Bacaicoa, & Sullivan, 1998). Larger trees are associated with decreased crime, as they signal the presence of informal/formal social control in neighborhood and increase the risk of committing crime (Donovan & Prestemon, 2012; Wolfe & Mennis, 2012).	Audited as continuous numeric responses and categorized as absent/few (trees/shrubs ≤ 3) or some/dense (trees/shrubs > 3).
Personalizations on the property; House or yard decorations; Garden; Lawn in poor condition; Place to sit outside; Signs of dog	Those territorial functioning features reflect pride of ownership and territoriality, relate to residents' perceptions of safety, and have been linked to increased social interaction and sense of community (Perkins et al., 1993).	1. Personalizations and Decorations were audited as continuous numeric responses and categorized as to categories. · Personalizations: ≤1 or >1. · Decorations: ≤3 or >3. 2. The below factors were audited as categorical responses. · Garden: Yes or no. · Lawn in poor condition: Yes or no. · Place to sit outside: Yes or no. · Signs of dog: Yes or no.
Defensible space		
Barrier	A symbolic or real barrier, such as fence, wall, or hedge can promote residents' responsibility to secure and maintain a safe and well maintained block, and further discourage crime (Cozens & Love, 2015; Perkins et al., 1992).	Audited as categorical responses: absent, on property (barrier is part of the property), or on perimeter (barrier is around the perimeter of the entire property).
Security bars on windows and doors	Crime opportunities can be reduced through environmental modification (Cornish & Clarke, 2003; Cozens & Love, 2015). Presence of security bars or gates on windows or doors can physically deter entry by criminals (Cozens & Love, 2015; Perkins et al., 1992).	Audited as categorical responses: yes or no.

4. Analysis and results

4.1. Poisson regression analysis

The results of estimating the Poisson model for violent crime are shown in Table 4. A backward stepwise approach was used to specify the model, retaining all variables that were statistically significant at least at the conventional 0.05 level of significance. The goodness of fit of the model is summarized by a Pseudo R^2 of 0.530. An extreme low value of Moran's I in residuals (0.003) with an insignificant Z score (0.366) indicates that spatial autocorrelation has been successfully removed from model residuals by the spatial filter. An over-dispersion parameter (2.066) was calculated to correct the intervals of confidence (for more details, see Moniruzzaman & Páez, 2012b).

The final model consists of eight significant variables all with signs as expected. Concretely, percent of population below the poverty level is significant and positive, while percent of population with bachelor's degree is significantly negative. This indicates that BGs with higher poverty rate tend to have more violent crime, while BGs with higher educated population tend to have less violent crime. Percent of foreign-born population has a significantly negative relationship with violent crime, which indicates that BGs with higher immigrant concentration experience lower violent crime. This is in agreement with the "immigrant revitalization" argument (Lee & Martinez, 2002; p. 365). Percent of renter-occupied housing units is significantly positive, which suggests that BGs with more rental residences experience more violent crime. Single-parent family has a statistically significant and positive relationship with violent crime, which indicates that BGs with more disrupted families tend to experience more violent crime. Population density is significant and negative, thus indicating that higher population density in neighborhoods can contribute to significantly reduce violent crime. Percent of vacant housing units is significantly positive, which indicates that BGs with more vacant properties experience increased violent crime. Young male population is significant and positive, which as expected suggests that BGs with higher young male population (15 to 24) tend to experience more violent crime. Among these variables, educated population is the strongest predictor in the model, while percent of vacant properties is the second strongest one. Population density and young male population have the least effect on violent crime, compared to other significant predictors.

Table 4
Parameter estimates from the Poisson regression with spatial filter (the dependent variable is count of violent crime in 2002).

Variable	Coefficient	p-Value
Constant	1.013	0.000
Socio-economic deprivation		
% of population below the poverty level	0.006	0.012
% of population with bachelor's degree	−0.023	0.000
% of unemployed population	–	–
Ethnic heterogeneity		
Heterogeneity index	–	–
% of foreign-born population	−0.010	0.028
Residential mobility		
% of renter-occupied housing units (*suitable targets*)	0.010	0.000
% of population living in the same house as 5 years ago	–	–
Family disruption		
# of single-parent families	0.003	0.000
Guardianship		
population density (in thousands)	−0.081	0.000
% of vacant housing units	0.017	0.000
Motivated offenders		
# of young male population age 15–24 (log transformed)	0.146	0.002
Spatial filter (16 eigenvectors)	1.000	0.000
Pseudo R^2	0.530	
N	567	
Moran's I of residuals	0.003	
Z score for Moran's I	0.366	
Over-dispersion parameter (estimated)	2.066	

The spatial filter is synthesized in the usual way from 16 eigenvectors to yield a coefficient of 1. Selection of the eigenvectors was based on their ability to reduce the degree of residual spatial autocorrelation below significance. A detailed selection procedure can be found in Moniruzzaman and Páez (2012a). As seen in Fig. 4, the distribution of the spatial filter is fairly symmetrical. The top and bottom quantiles used for selection of BGs below are also shown there.

It is important to note at this point the time lag between the data used for analysis (2002) and the imagery used for the virtual audits. The results of the analysis could be biased if the results differed greatly between our 2002 model and a hypothetical model estimated using 2007 data (which unfortunately were not available). Previous research (He et al., 2015) shows that the parameters of models tend to be stable over time. As shown in Fig. 3, five regression lines, labeled as A, B, C, D, and E, indicate the relationships between crime of five single years and socio-economic characteristics. Stability of the coefficients means that the lines do not significantly change in the span of time covered. This gives us confidence that the relationships modeled are robust to the time lag between the audits and the modeling. Other research, moreover, has also shown that the distribution of hot spots of crime are also temporally persistent. Use of the tertiles also provides a robust alternative to selection of the audit sites, since tertiles are unaffected by outliers.

4.2. Selection of audit sites

For selection of sites for audits we classify the spatial filter into three quantiles, each containing 189 BGs (see Figs. 4 and 5). Auditing an entire BG can be burdensome, therefore, in this study we first sampled a number of BGs, from which we then selected blocks and individual properties for environmental audit. In order to have a sufficient sample size of around 300 blocks for contingency table analysis, we sampled 17 BGs from Q1 and 16 BGs from Q3. The BGs were sampled in such manner. We first classify the over- and under-predicted BGs into 5 quantiles respectively. Then sort each quantile by the number of crime count. In each quantile, we select approximately 3 BGs from the top. When one BG is selected from a quantile in Q1, the other BG having similar number of crime count is selected from the same quantile of Q3. During this process, we keep in mind that the selected BGs should be randomly distributed in the two Quantiles and the city. Also, the selected BG should have enough blocks for us to sample in the next step.

From those 33 BGs, we sampled 169 blocks from Q1 where we expect to find more crime-hindering factors; 162 blocks from Q3 where we expected to find more crime-facilitating factors. This generates a total of 331 blocks, which is a sufficient sample size for contingency table analysis. These 331 blocks is sampled in the same manner of control-case studies as stated above.

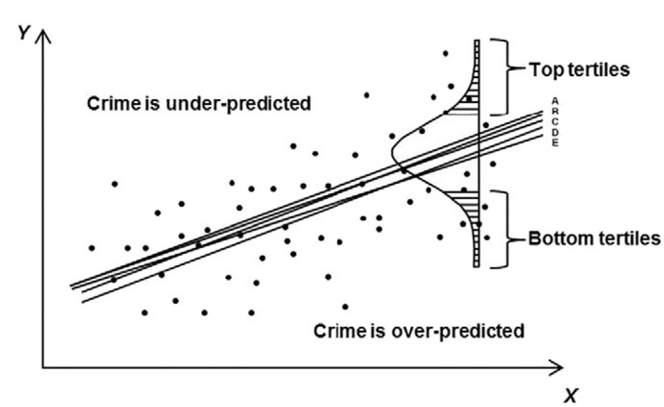

Fig. 3. Temporally stable regression lines and effect on site selection.

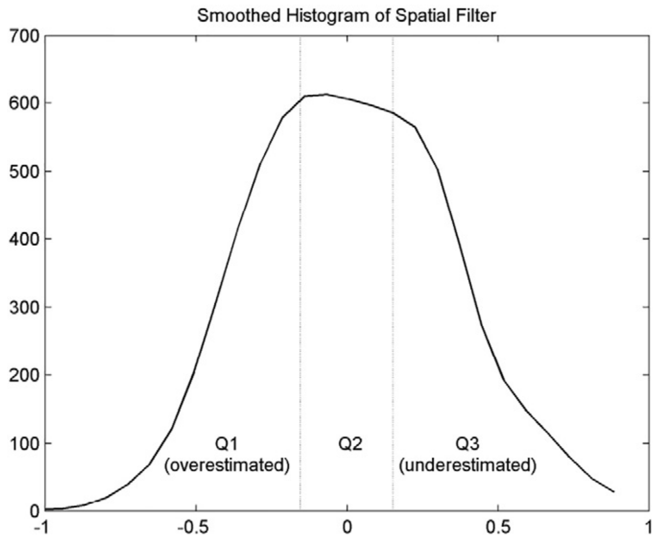

Fig. 4. Smoothed histogram of spatial filter.

There are only 9 environmental factors need to be audited at block level. 18 more factors need to be audited at individual property level. Therefore, from those selected blocks, we then sampled 459 individual residential properties: 230 from over-predicted blocks and 229 from under-predicted blocks. This sampling process follows the instruction of RBEI. That is, if there are eight or fewer residential properties on the entire block, then audit every property. If there are more than eight residential properties, evaluate every third house or apartment building. Fig. 5 shows that the selected BGs are randomly distributed across two quantiles. As the selected blocks and individual properties are within those BGs, they are also randomly distributed across two quantiles.

4.3. Environmental audit using Google Street View

The first author conducted the virtual audit in September 2015. Using the desktop data collection tool with the RBEI embedded, the factors listed in Tables 3 and 4 were identified from GSV. To avoid biasing the audits, blocks (and individual properties) from over- and under-predicted BGs were merged into a single shapefile so that at the time of the audits the auditor was not aware of the block's status as Q1 or Q3.

For most audit sites in Columbus, Google provides historical street view images available for several dates, for example, August 2007, May 2009, June 2011, June 2012, June 2014, August 2015, and November 2015. To minimize the interval between our crime data and GSV images, we collect physical features mainly from images drawn from August 2007. Images from 2009 were used <3% of the time, and only when 2007 images were absent for some blocks, the resolution of 2007 images was too coarse to identify certain environmental features, or environmental features (such as outdoor lights) were blocked by trees. The study by Clarke et al. (2010) indicates that a five-year interval can provide reliable environmental indicators. This is reinforced by more recent research. For instance, Gullon et al. (2015) discuss the use of GSV images captured between 2008 and 2014 and on-site audits in 2014. They conclude that the agreement between audits is very high for a number of items, including (similar to our study) garden maintenance, verge maintenance, and cleanliness. Mooney et al. (2014) look specifically at measures of disorder, and find that even with temporal lags, virtual audits can provide reliable and valid measures of social disorder, including the following items: 1) garbage, litter, broken glass; 2) bottles or cans; 3) evidence of graffiti; and 4) abandoned cars.

Fig. 5. Selected BGs from Q1 and Q3, target blocks and properties are selected from those BGs.

4.4. Contingency table analysis

The dBASE table of the shapefile that contains observed environmental factors was analyzed using contingency tables. In the dBASE table, a number of environmental factors were recorded as categorical responses (e.g., absent or present). Other continuous responses (e.g., percent of dilapidated exterior) were categorized for analysis. Contingency tables display the frequency distribution of observed cases from both Q1 and Q3. A chi-square (χ^2) test can be implemented to compare the observed frequency of each cell to the expected frequency under the null hypothesis of independence.

Tables 5 present the summary result of analysis of environmental factors. The null hypothesis of independence is rejected for 20 environmental factors at least at the 0.05 level of significance, but the null hypothesis is accepted for one factor that captures territorial functioning.

Table 5
Summary of environmental factors using χ^2 independence tests.

Environmental factors	Chi-square statistic	*p*-Value
Physical incivility		
Graffiti	48.524	0.000
Damage on street property	55.610	0.000
Potholes in the street	59.261	0.000
Unsecured abandoned buildings	29.478	0.000
Secured abandoned buildings	92.985	0.000
Abandoned cars	17.791	0.000
Litter	156.311	0.000
Dilapidated exterior	30.476	0.000
Roof condition	81.260	0.000
Cracked brick or concrete	104.454	0.000
Broken windows or fixtures	27.005	0.000
Territorial functioning		
Block or crime watch signs	20.065	0.000
Trees or shrubs	8.336	0.004
Personalizations on the property	4.518	0.034
House or yard decorations	35.195	0.000
Garden	66.465	0.000
Lawn in poor condition	33.885	0.000
Place to sit outside	2.465	0.116
Signs of dog	5.649	0.017
Defensible space		
Barrier	62.902	0.000
Security bars on windows and doors	65.050	0.000

Table 6
Physical incivility factors analyzed using contingency (Table 1).

		Graffiti		Property damage		Potholes in the street		Total
		Absent	Present	Absent	Present	Absent/few	Some/dense	
Q1	Count	144	25	152	17	155	14	169 ∗ 3
	Expected	114.4	54.6	121.5	47.5	124.1	44.9	
Q3	Count	80	82	86	76	88	74	162 ∗ 3
	Expected	109.6	52.4	116.5	45.5	118.9	43.1	
	Total	224	107	238	93	243	88	331 ∗ 3

Of these significant factors, 11 factors that capture physical incivility are significant, seven factors significantly capture territorial functioning, and two factors significantly describe defensible space. Tables 6 to 13 in the Appendix show these factors analyzed using contingency table.

Physical incivility is measured by 11 factors listed in Tables 6 to 9. Observed frequencies of the presence of graffiti, property damage, potholes in the street, abandoned buildings, and abandoned cars are significantly lower than expected in audit sites of Q1 (where there is less crime than predicted by the model), but significantly higher than expected in audit sites of Q3 (where there is more crime than predicted by the model). It can be seen that for audit sites in Q1, the presences of some/dense litter, some/dense dilapidated exterior, roof needs repair, broken windows or fixtures, and cracked brick are significantly lower than expected. However, these features significantly exceed the expectation for audit sites in Q3. The frequency of properties with new roof is significantly prevalent in Q1.

Factors listed in Tables 10–12 capture territorial functioning. As shown in Table 10, for audit sites in Q1, the presence of crime watch signs is significantly prevalent. For sites in Q3, the observed presence of crime watch signs is significantly lower than expected. Observations of some/dense trees are more frequent than expected in audit sites in Q1, but absent/few trees are more frequently observed than expected in sites in Q3. As shown in Tables 11 and 12, for properties in Q1, the frequency of properties with more than one personalization, more than three house or yard decorations, and the observed presence of garden is significantly higher than expected. The presence of properties with poor lawn condition and signs of dog is significantly prevalent. The factor of place to sit outside on the other hand is not significant.

As listed Table 13, defensible space is measured by barriers and security bars on windows and doors. Barrier can be wall, fence, or hedge of any sort or height. For properties in Q1, the frequency of properties with barrier around the perimeter, and properties with security bars on windows is significantly higher than expected. The presence of properties without barrier is significantly less than expected. For properties in Q3, in contrast, the presence of properties with no barrier and properties with no security bars is more prevalent.

Table 7
Physical incivility factors analyzed using contingency (Table 2).

		Unsecured abandoned buildings		Secured abandoned buildings		Abandoned cars		Total
		Absent	Present	Absent	Present	Absent	Present	
Q1	Count	157	12	138	31	158	11	169 ∗ 3
	Expected	137.9	31.1	94.5	74.5	144.5	24.5	
Q3	Count	113	49	47	115	125	37	162 ∗ 3
	Expected	132.1	29.9	90.5	71.5	138.5	23.5	
	Total	270	61	185	146	283	48	331 ∗ 3

All of the significant environmental factors lend support to our hypotheses presented in Tables 3.

First (see Fig. 6), we find more built environment factors that hinder crime in BGs where observed crimes are less than predicted (Q1, Green Zones). Fig. 7 shows examples of these physical factors: barriers are more frequently observed, along with security bars/gates, yard decoration, personalization signs of house number, good roof condition, crime watch sign and dog sign; where as a less frequent presence of abandoned building, car, graffiti, dense litter, poor condition of lawn, dilapidated exterior and broken windows.

Second, we generally find more built environment factors that facilitate crime in BGs where observed crimes exceed the expectation (Q3, Red Zones). Fig. 8 shows examples of physical signs of environmental decay found through GSV: abandoned buildings and cars are more frequent, as are graffiti, dense litter, poor condition of lawn, dilapidated exterior and broken windows. On the other hand, there is a dearth of barriers, security bars/gates, house decoration and personalization, crime watch signs, and signs of dog.

Although caution needs to be exerted when interpreting more ephemeral physical signs such as litter and graffiti, many studies suggested that there's a time-lag effect of socio-economic fluctuation on crime (Rosenfeld & Fornango, 2007), and crime itself can in turn impact socio-economic outcomes (Malby & Davis, 2012). In light of this, we conjecture the presence of a similar time-lag effect of environmental decay on crime, and a similar time-lag effect of crime on physical decay of residential environment. This is an issue in need of further research.

5. Discussion and conclusion

An important shortcoming in criminological research, that considers the effect of built environment on crime, is the lack of fine-scale quantitative data of the built environment. It is desired to develop an efficient and cost-saving approach for collecting high quality environmental data. To address this issue, we develop an environmental audit approach using GSV. Based on this approach, we investigate the

Table 8
Physical incivility factors analyzed using contingency (Table 3).

		Litter		Dilapidated exterior		Roof condition			Total
		Absent/few	Some/dense	Absent/few	Some/dense	New	Average	Needs repair	
Q1	Count	212	18	198	32	91	127	12	230 ∗ 3
	Expected	147.8	82.2	172.4	57.6	59.1	126.8	44.1	
Q3	Count	83	146	146	83	27	126	76	229 ∗ 3
	Expected	147.2	81.8	171.6	57.4	58.9	126.2	43.9	
	Total	295	164	344	115	118	253	88	459 ∗ 3

Table 9
Physical incivility factors analyzed using contingency (Table 4).

		Broken windows or fixtures		Cracked brick or concrete		Total
		Absent	Present	Absent	Present	
Q1	Count	213	17	191	39	230 ∗ 2
	Expected	192.4	37.6	137.3	92.7	
Q3	Count	171	58	83	146	229 ∗ 2
	Expected	191.6	37.4	136.7	92.3	
	Total	384	75	274	185	459 ∗ 2

Table 10
Territorial functioning factors analyzed using contingency (Table 1).

		Crime watch signs		Trees or shrubs		Total
		Absent	Present	Absent/few	Some/dense	
Q1	Count	127	42	39	130	169 ∗ 2
	Expected	141.9	27.1	51.1	117.9	
Q3	Count	151	11	61	101	162 ∗ 2
	Expected	136.1	25.9	48.9	113.1	
	Total	278	53	100	231	331 ∗ 2

relationship between residential built environment and violent crime in this paper. Results obtained from Poisson regression with spatial filtering and GSV-based environmental audit inform several theoretical and practical implications. The implications, contributions and limitations are summarized as follows.

5.1. Implications for research

The theoretical implications are as follows. First, this study indicates that the filtered spatially auto-correlated parts from model residuals provides important information of systematic over- and under-estimation of the dependent variable, which can be utilized to further explore the relationship between omitted variables and the dependent variable. Second, this study contributes uniquely to existing criminological literature by using the GSV to collect fine-scale quantitative data of built environment. Third, the Poisson model with spatial filter provides a number of significant social-economic correlates of violent crime. The effects of said correlates on violent crime are consistent with previous studies in other settings. This finding not only adds credibility to SDT and RAT, but also supports that a combination of the two theories provides relatively comprehensive understanding of violent crime. Fourth, the GSV-based audit provides an alternative way to re-evaluate influential theories of crime. Significant environmental factors identified from GSV lend support to BWT and CPTED. Fifth, consistent with previous studies (e.g., He et al., 2016), the finding regarding the negative effect of immigrant concentration on violent crime lends empirical support to the “immigration revitalization” hypothesis proposed by Lee and Martinez (2002, p. 365).

Table 11
Territorial functioning factors analyzed using contingency (Table 2).

		Personalization		Decorations		Garden		Total
		≤1	>1	≤3	>3	No	Yes	
Q1	Count	207	23	87	143	39	191	230 ∗ 3
	Expected	213	17	118.8	111.2	80.7	149.3	
Q3	Count	218	11	150	79	122	107	229 ∗ 3
	Expected	212	17	118.2	110.8	80.3	148.7	
	Total	425	34	237	222	161	298	459 ∗ 3

Table 12
Territorial functioning factors analyzed using contingency (Table 3).

		Poor lawn condition		Place to sit outside		Signs of dog		Total
		No	Yes	No	Yes	No	Yes	
Q1	Count	189	41	18	212	171	59	230 ∗ 3
	Expected	160.3	69.7	23.1	206.9	181.4	48.6	
Q3	Count	131	98	28	201	191	38	229 ∗ 3
	Expected	159.7	69.3	22.9	206.1	180.6	48.4	
	Total	320	139	46	413	362	97	459 ∗ 3

5.2. Implications for practice

The practical implications of our research can be summarized as follows. Environmental factors identified from GSV-based audit provide insights for CPTED initiatives, situational crime prevention efforts, and urban renewal projects. Police portal should be encouraged for neighborhoods presenting public signs of physical disorder. What's more, the identified socio-economic correlates also indicate that more police resources are required by neighborhoods with high percent of rental and vacant residences. This study provides empirical test of GSV for the purpose of virtually identifying environmental correlates of violent crime. We find that GSV-based audit can reduce both human cost and travel expense, protect auditors from potential risks, and allow quantitative environmental data to be collected in a systematic way.

5.3. Contributions

This study presents a unique method which allows fine-scale environmental data be collected in a systematic way. Compared to conventional study of built environment and crime, this study indicates that after controlling for socio-economic correlates (and possibly meso-scale environmental factors), the hindering and encouraging effects of the finer-scale physical features of built environment on violent crime can be measured more accurately and effectively.

Compared to conventional methods of site selection and environmental audit, this study has several contributions. (1) A model-based site selection method has proved its efficiency in determining “where” to audit. (2) Model estimation with spatial filtering approach indicates that eigenvector spatial filtering can not only help to produce model estimates that are not biased by spatial autocorrelation, but also help to make further hypotheses based on an analysis of the systematic patterns in model residuals. (3) The desktop and electronic version of RBEI can be reused in future environmental assessment of various purposes. (4) The GSV-based audit has proved effective in answering the question of “how” to audit. Compared to conventional on-site audit, this study has proven that GSV can benefit future studies in a number of ways as follows.

First, when the study sites are dispersed across a large city, on-site audit can be challenging and costly. However, in this case, GSV-based virtual audit can reduce transportation time and cost and increase efficiency. Second, compared to on-site observation which suffers from

Table 13
Defensible space factors analyzed using contingency table.

		Barrier			Security bars on windows and doors		Total
		Absent	On property	Perimeter	No	Yes	
Q1	Count	14	89	127	52	178	230 ∗ 2
	Expected	47.1	83.7	99.2	66.1	163.9	
Q3	Count	80	78	71	80	149	229 ∗ 2
	Expected	46.9	83.3	98.8	65.9	163.1	
	Total	94	167	198	132	327	459 ∗ 2

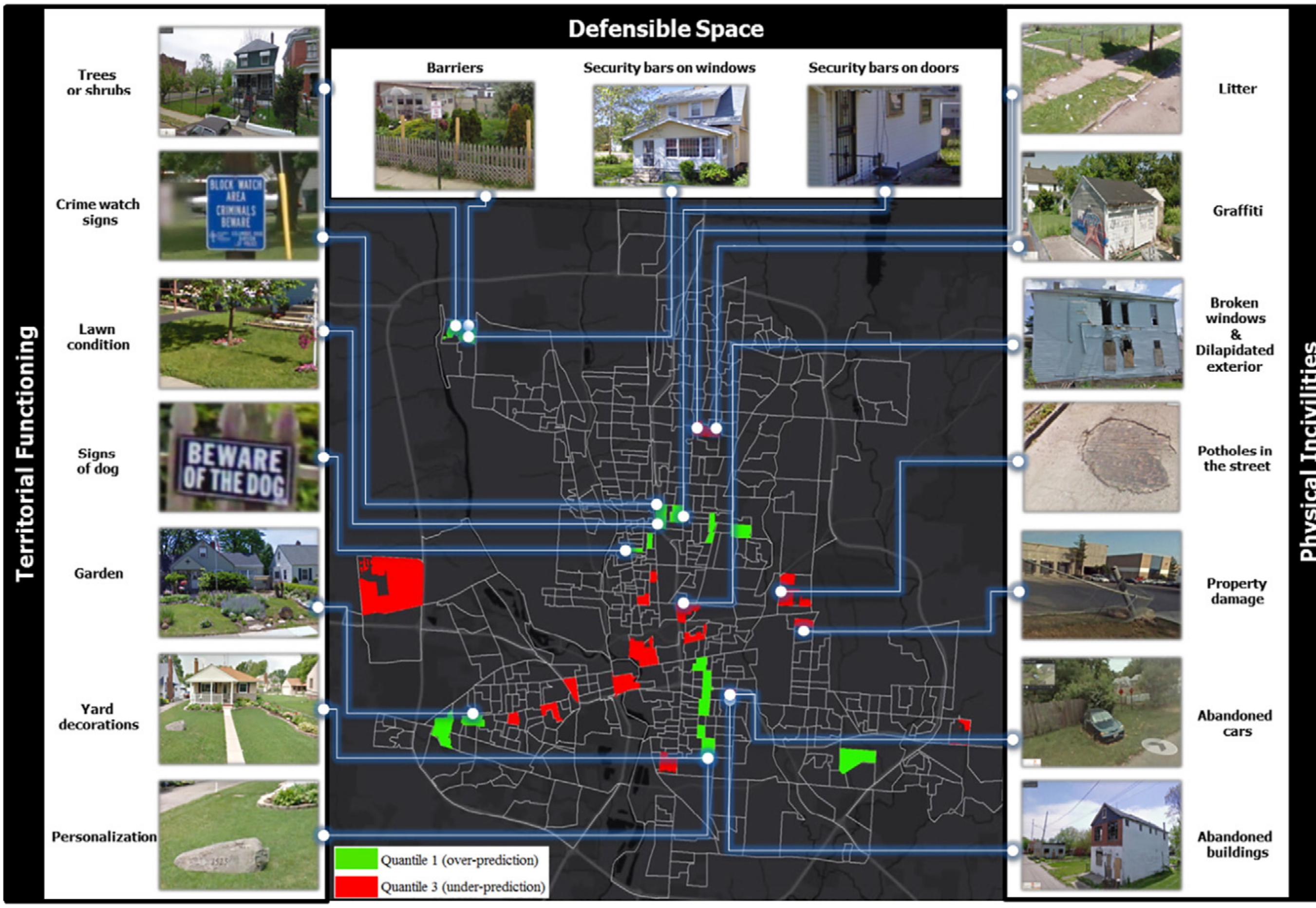

Fig. 6. Summary of significant environmental correlates of violent crime identified from Google Street View. Correlates linked to green zones are crime-hindering factors which are more frequently found in BGs where observed crimes are less than predicted (Q1). Correlates linked to red zones are crime-facilitating factors which are more frequently found in BGs where observed crimes are more than predicted (Q3).

temporal fluctuation of environmental features, GSV provides a unified data source for studies of various purposes. The present and historical GSV images are provided with date stamps (month and year). Results obtained from GSV-based audit are comparable and can be cross-validated. Third, in-person field audit in high crime neighborhoods may put auditors at risk. However, GSV-based audit allows auditors remotely and virtually observe the study sites without taking any risk.

5.4. Limitations

This study also presents several limitations that need to be addressed in future study. One limitation is that virtual audits for smaller items. As noted by Clews et al. (2016), GSV is reliable when capturing many aspects of the built environment, though less effective for small items (e.g., litter, small signs), more ephemeral social activities (e.g., alcohol consumption), and those that vary by time of the day (e.g., loitering). It is worthwhile to note, however, that the results for these small items are still statistically significant in our case study. The other potential limitation is the variability in the timing of capture of the GSV images. Regarding this matter, Curtis et al. (2013) find that the timing of images in GSV changes but that it tends to change more rapidly near intersections. They do not show, however, that the temporal variation in the time the images were captured is associated with large differences in the content of the images.

In addition, it bears mentioning that the findings of this study are limited to violent crime. Previous studies have empirically demonstrated the role of built environment in affecting disaggregated violent crimes such as homicide and robbery (e.g., Lasley, 1996; Webb & Laycock, 1992), and property crimes such as residential burglary (Breetzke, 2012) and auto burglary (Michael, Hull, & Zahm, 2001). Future studies are needed to replicate present analyses in those settings to evaluate the applicability of the proposed method.

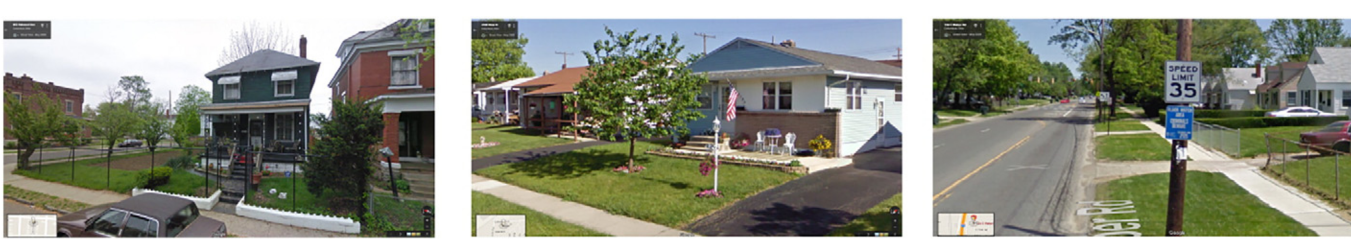

Fig. 7. Examples of crime-hindering environment factors found in GSV images. The left image shows barriers, security bars on windows, and yard decoration. The middle image shows personalization sign of house number, and good lawn and roof condition. The right image shows neighborhood crime watch sign.

Fig. 8. Examples of physical signs of environmental decay found in GSV images. The left image shows abandoned building, graffiti on the door, and dense litter. The middle image shows abandoned cars, and poor condition of lawn. The right image shows abandoned building, dilapidated exterior, broken windows, dense litter, and poor condition of lawn.

5.5. GSV for future research

The availability of historical GSV provides opportunities for other future studies such as time series study of built environment, comparative study of present landscape with historical environment. Images of different time nodes (e.g., August 2007, May 2009, June 2011, June 2012, June 2014, August 2015, and November 2015) are comparable. Similar to time series analysis of optical remote sensing data, environmental characteristics can also be observed from historical GSV images and can contribute to study the temporal dynamic variation of urban landscape. In addition to exclusively using GSV images, one can also take a mobile device and walk into the field. This allows the GSV-based virtual audit and on-site observation to be conducted simultaneously. The present urban landscapes can be directly compared with historical environment.

GSV brings opportunities and challenges simultaneously. Challenges of using GSV include: First, although the coverage of GSV images has been dramatically increased in recent years, its spatial completeness cannot be guaranteed in every street segment and every city. Although in our study GSV provided images of front and back yards for most blocks, which gives us confidence about the accuracy of quantity of physical features in our audits, it is likely that in other settings, some aspects of properties cannot be observed from GSV images. Future studies planning to conduct virtual audit using GSV need to preliminarily examine the availability of GSV in their study sites first. Second, although historical GSV images are time stamped, time interval between historical images varies upon individual study areas. Third, previous studies suggest that the reliability of fluid physical features (e.g., the presence of litter and graffiti) can be relatively lower than more stable features (e.g., block watch signs, trees on the property). Maintaining the contemporaneity of GSV data and crime data can help to reduce potential bias results from temporal instability of physical features.

Acknowledgments

The authors would like to acknowledge the editor and anonymous reviewers for their insightful and constructive comments. The authors would also like to acknowledge Dr. Shiguo Jiang for his sharing of crime data and Mr. Zhiyao Huang for his assistance in developing the desktop RBEI tool.

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