Implications of Urban Planning Variables on Crime: Empirical Evidences in Seoul, South Korea[1]

PARK JongHoon[1], LEE SeongWoo[1], LIM HyngBaek[2]
[1]*Program in Regional Information, Seoul National University*
200-8211,Daehak dong, Kwanak Gu, Seoul
South Korea
pjh1983@snu.ac.kr, seonglee@snu.ac.kr

[2]*Program in Community Development, Sungkyul University*
Sungkyul 53st., MaanGu, AnyangSi
South Korea
emperor10131@hotmail.com

Abstract

The present study investigated the determinants of crime incidence in Seoul Metropolitan Area (SMA) of Korea, focusing particularly on spatial planning effects on crime incidence. Since crime incidence is in general closely related to the spatial characteristics of a city, we applied diverse spatial econometrics models (SAR, SEM, SAC, GWR, Mixed GWR) to incorporate the regional characteristics into the statistical models. The spatial planning variables adopted in this study are residential concentration, mixed land use, concentration of crime prevention facilities and spatial accessibility. We found that residential concentration seems to work in diminishing crimes. Mixed land use plays a positive role in reducing crimes. Concentration of crime prevention facilities also has a positive effect on lowering crimes. Spatial accessibility showed a positive effect on crime occurrence. The present study concludes with some policy suggestions that can alleviate crime incidence focusing particularly on urban planning perspectives.

Key words: Crime Determinants, Spatial Planning, Spatial Econometrics Models, Seoul Metropolitan Area

JEL Classification: R00

The Very Preliminary Draft Not Ready for Citation

1 Introduction

Theoretical arguments to explain criminogenic events and environments from western experiences deliver such social and economic factors as race, age, gender, income inequality, education, poverty, social exclusion as major covariates to determine crime incidence (Buonanno, 2006). Some recent developments have also been made in the field of geographical and political factors which include (mixed) land use, residential concentration, political structure, presence of deterrent public activities like distribution of police (Browning et al. 2010; Yoon and Joo, 2005).

While massive interest of criminal studies is still focusing on motivation of offenders and

[1] Corresponding author, Program in Regional Information, Seoul National University, Seoul, Korea, 151-921, Email: seonglee@snu.ac.kr

avoidance of victimization in the micro perspective, there have been some theoretical developments handing priority to space as a direct factor that influences crime incidence. The empirical applications of this perspective can be found in Cahill and Mulligan (2007), and Stucky and Ottensmann (2009). This approach may be more insightful for policy makers if major concern is to understand crime rather than criminality since public policy concerns more on crime prevention instead of offender control.

Crime incidence is not uniformly distributed over space, an argument that can date back over a century (Eck and Weisburd, 1995). However, it is Chicago ecological school represented by Shaw and McKay (1942), to initiate identifying the relationship between spatial factors and crime incidence in a robust academic insight (Herbert, 1982). The prime question in this perspective is what spatial conditions determine regional variations in crime rates. The relationship between spatial factors and crime has been investigated in diverse geographical contexts (Blau and Blau, 1982; Brantingham and Brantingham, 1995; Goudriaan et al., 2006; Hooghe et al., 2011). These studies have the common assumption that diverse spatial factors have direct effects on crime incidence irrespective of national and/or cultural contexts.

Recognition of space to crime is not new. Increasing concerns on spatial characteristics of crime causality are widespread in western societies (cf. Eck and Weisburd, 1995) however, much less known are empirical evidences of crime incidence from Asian countries including South Korea. Do these explanations hold for other countries that have quite heterogeneous historical and cultural backgrounds? This question is particularly relevant if we see the empirical evidences from Clinar (1978). In a rare attempt at comparative analysis, Clinar (1978) showed that there exists pronounced differences in crime rates between the US and Switzerland that can not be explained by general argument of crime theories. Hooghe et al. (2011) also argued that a construct to explain crime incidence that is true for one country can not be applied to another country.

Spatial impacts on crime incidence can be controlled by spatial planning schema operated by diverse levels of government intervention. Although it is impossible that a spatial planning practice takes all the spatial impacts into account, key factors closely related to crime incidence can be managed through spatial planning practices. Therefore, an attempt is required to investigate the relationship between major spatial planning factors and crime incidence.

The present study aims to empirically analyze prevalence of crime in Seoul Metropolitan Area (SMA) to understand the relationship between spatial factors and crime incidence. We applied diverse spatial econometrics models to identify the decisive factors between crime incidence and spatial planning factors. Spatial planning variables adopted in this study are residential concentration, mixed land use, concentration of crime prevention facilities, and spatial accessibility. These four variables are traditional factors that form spatial planning in that they all consider or reflect the land use, transportation system, location and density of residential areas, and physical structure of facility planning. Based on the findings from these analyses on the relationship between the factors that frame spatial planning and the crime incidence, the present study will suggest some implications for spatial planning to prevent crime.

The present study pays particular attention to the recent development of spatial econometrics modeling in the field of criminology perceiving the fact that covariates to determine crime incidence can be performed differently in different spaces (Brownning et al., 2010; Cahill and Mulligan, 2007; Hipp, 2007; Hooghe et al., 2011). These studies show that ignorance of the possibility of spatial differences between covariates and crime incidence can result in the violation of the basic assumption (i.e., independence of observation) of many standard statistical models since the presence of spatial dependence and spatial autocorrelation is widespread in most spatial data (Anselin, 1988). Cahill and Mulligan (2007) also argue that applying spatial data in ecological studies of crime is useful even when the existence of local processes is not theoretically identified. Following these insights, we seriously take the potential for spatial heterogeneity of crime incidence of Seoul metropolitan area into our modeling consideration.

2 Background

Since increasing trend of crime prevalence is one of the major factors that impede social developments, lots of attention has been paid to crimes in the field of diverse social sciences including criminology. Traditionally, major attention was placed on the detection and apprehension of actors committing crimes, while much more efforts are currently being made to understand macroscopic factors that influence crimes such as social, economic, and institutional factors.

Macroscopic explanations on crime in sociology that explains the crime factors vary. Social disorganization theory is one of the most widely recognized sociological theories. Suggested by Shaw and Mckay (1942), the theory assumes that crime is closely related to social disorganization, a phenomenon losing a collective, voluntary control by lacking social solidarity and integrity. Factors including poverty, residential mobility, diversity of races and ethnic groups, population density, family disorganization, and single parent family are commonly adopted to measure the extent of collective control of a community. Many studies have focused on these factors to investigate their relationship with crime incidence. It is commonly accepted and reported that social disorganization is closely related to crime incidence (Petee and Kowalski, 1993; Petee et al., 1994; Warner and Pierce, 1993; Witt, et al., 1999; Sampson and Groves, 1989; Warner and Pierce, 1993; Barnet and Mencken, 2002).

Another representative theory that explains crime determinants in sociological perspective is routine activity theory. Suggested by Cohen and Felson (1979), the theory focuses on the local environment and circumstantial conditions. According to this theory, crime occurs when crime offenders and targets exist while the circumstantial conditions are lack of controls that can deter the crime (Paulsen and Robinson, 2004). If any of the three conditions is not satisfied, crime never occurs. This theory has everything to do with spatial planning factors, as the spatial planning can immediately aggravate or improve the circumstantial conditions.

Economic approaches in crime assume that there is a close relationship between crime and the opportunity of economic activity (Mocan and Rees, 2005; Corman and Mocan, 2005). In other words, based on the rational expectation hypothesis, they insist that crime occurs when much more benefits are expected than the costs (Becker, 1968). Economic approaches can be largely divided into microscopic and macroscopic approaches. While the former focuses on the individual criminals' behaviors, the latter stresses the importance of economic condition of the community or region such as unemployment and income disparities, etc. It is widely reported that the less economically activated a region or community is, the more the crime occurs and the theory has been supported by many empirical applications in diverse contexts (Sampson and John, 1987; Hooghe et al., 2011; Andressen, 2006; Ceccato et al., 2002; Lee and Cho, 2006; Chun and Park, 2008).

The pioneering perspective pursuing crime prevention through the lens of spatial planning is the defensible space theory suggested by Newman (1973). This theory approaches crime prevention strategies from an architectural standpoint, insisting that extensive control of territoriality, natural surveillance, image, and milieu can prevent and decrease crime. More recently, crime prevention through environmental design (CPTED) has emerged as an important strategy for crime prevention planning. CPTED is a strategic approach to deter crime and reduce the fear of crimes through appropriate design and effective use of architectural environment. Interests on CPTED have been increased in Korea as well as western countries. Incorporating these perspectives, a number of studies have been made focusing on the impacts of spatial planning factors on crime incidence. It has been proven that the spatial factors described above have immediate impacts on crime. Spatial factors that have earned much of the research interests were spatial connectivity (Hiller and Shu, 2000; Cozens and Love, 2009; Johnston and Bowers, 2010), mixed land use (Taylor et al., 1995; Novak and Seiler, 2001; Lockwook, 2007), zoning (Paulsen, 2011), and public spaces such as parks and pedestrian paths (Chapin, 1991; Hilbron, 2009).

There has been handful of crime studies about the crime incidence of Korea to be published in international society (Yoon and Joo, 2005; Chang, 2009). However, these studies merely focused on the crime determinants in the sociological perspectives, not investigating the determinants from spatial planning perspectives. Also, they are limited in that they assume covariates of crime are invariant over space. This assumption may be too much since many prior studies on crime in diverse contexts have witnessed evidence of spatial dependencies and heterogeneities (Baller et al., 2001; Browning et al., 2010; Cahill and Mulligan, 2007; Hipp, 2007; Morenoff et al., 2001). While many preceding studies in Korea have failed to consider the spatial heterogeneity on their analytical models, the present study investigates the spatial factors affecting crime incidence while taking spatial dependence of crime incidence into account. Also, the present study aims to demonstrate location-specific characteristics of relationship between spatial planning factors and crime incidence, which has long been of a particular interest in the worldwide perspective.

3 Methodology and Data

1. Methodology

1) Validity of Spatial Econometrics Model

Theories to explain the causes of crime are largely divided into microscopic and macroscopic methods. The former focuses on individuals or actors while the latter puts more emphases on social and structural factors. This categorization makes sense from the data structure viewpoint as individual crime data belongs to microscopic while data on specific areas or nations belongs to macroscopic. In analyzing crime prevalence with macroscopic data at regional scale, consideration of spatial characteristics on crime incidence is critical. Crime is closely related to the space or spatial characteristics and tends to concentrate on specific spaces due to spatial interaction or dependence of geographies. Due to the reasons, the non-spatial model like ordinary least square (OLS) may lead to biased and inconsistent estimates (Anselin, 1988).

Spatial autocorrelation test is a method to validate the effectiveness of the empirical application of spatial econometrics models. There are several indexes for the autocorrelation test, but Moran's I, Geary's C and Getis and Ord's G are most widely used. The present study adopts Moran's I to test the spatial autocorrelation of crime incidence in our data. The result shows that geographical dependence of crime incidence is statistically significant at p<.01 (Table 1). The result verifies it is necessary to adopt spatial econometrics models for the present study. Among the various spatial econometrics models that can incorporate the characteristics of spatial dependency, the present study adopts three representative spatial econometrics models (SAR, SEM, SAC), GWR and mixed-GWR (MGWR) that are explained in the following section.

Tab. 1 Result of Spatial Autocorrelation Analysis

	Moran's I Index	p-value
Crime Incidence	0.032	0.003

2. Spatial Linear Regression Model

(1) SAR, SEM, SAC

The standard spatial econometrics models are SAR (Spatial Autoregressive Regression), SEM (Spatial Error Model) and SAC (General Spatial Model) that are explained in detail by LeSage (1999). They are same in their fundamental concept, but differ in the way they control spatial dependency and spatial autocorrelation.

The first model is the SAR as in Eq. (1). The model assumes observations that are near should reflect a greater degree of spatial dependence than those that are more distant from each other, where Y is an n x 1 vector of dependent variable and X denotes an n x k matrix of explanatory variables. W represents spatial weight matrix containing contiguity relations or functions of distance. The scalar ρ is a coefficient on the spatially lagged dependent variable, and β denotes a parameter vector estimated from explanatory variables.

$$Y=\rho W(Y)+X\beta+\varepsilon,\ \ \varepsilon\sim N(0,\sigma^2 I_n) \qquad \text{Eq.(1)}$$

The second model is the SEM represented by Eq. (2). The model is based on the assumption that the disturbances exhibit spatial dependence, where the scalar λ is a coefficient on the spatially correlated errors.

$$\begin{aligned} &Y=X\beta+u \\ &u=\lambda Wu+\varepsilon,\ \ \varepsilon\sim N(0,\sigma^2 I_n) \end{aligned} \qquad \text{Eq.(2)}$$

The third one in Eq. (3) is the SAC, which includes both spatial lag and spatially correlated error terms.

$$\begin{aligned} &Y=pW(Y)+X\beta+u, \\ &u=\lambda Wu+\varepsilon,\ \varepsilon\sim N(0,\sigma^2 I_n) \end{aligned} \qquad \text{Eq.(3)}$$

The correct interpretation of the estimated coefficients in SAR and SAC models involves a computation of direct, indirect, and total effects. These computations are extensively explained in LeSage and Pace (2009), so we will not reiterate these points here. The direct effect characterizes the average impact of a change in the explanatory variables on the dependent variable at the same location. The indirect effect characterizes the average impact of a change in the explanatory variables on the dependent variable in different locations. The total effect represents the sum of direct and indirect effects.

The SAR model expressed in Eq. (1) is rewritten to its reduced form in Eq. (4) through which the direct and indirect effects can be obtained. It can also be noted that the SAC model shares the same direct and spillover effect properties with the SAR model.

$$Y=(I-\rho W)^{-1}X\beta+(I-\rho W)^{-1}\epsilon \qquad \text{Eq.(4)}$$

The matrix of partial derivatives of the expectation of Y, $E(Y)$, with respect to the kth explanatory variable of X is,

$$\left[\frac{\partial E(Y)}{\partial x_{ik}} \cdots \frac{\partial E(Y)}{\partial x_{nk}}\right] = (I-\rho W)^{-1}\beta_k \qquad \text{Eq.(5)}$$

The diagonal elements of Eq. (5) represent direct effects, while the off-diagonal elements contain the indirect effects. Accordingly, the direct and indirect effects can be expressed as Eq. (6).

$$\begin{aligned} &\text{Direct effect}: \frac{\partial y_i}{\partial x_{ik}} = S_k(W)_{ii} \\ &\text{Indirect effect}: \frac{\partial y_i}{\partial x_{ik}} = S_k(W)_{ji},\ \forall i \neq j \end{aligned} \qquad \text{Eq.(6)}$$

where $S_k(W) = (I-\rho W)^{-1}\beta_k$ acting as a “multiplier” matrix that applies higher-order neighboring relations to X_k.

To identify spatial autocorrelation, it is important to define a spatial weight matrix, which represents the spatial effects. Spatial weight matrix defines spatial proximity based on the assumption that geographically adjacent areas have a high level of spatial interaction between them. The spatial weight matrix may vary in its types. Generally it is recommended to adopt a spatial weight matrix to verify whether the spatial effects are appropriately reflected by comparing the results from the application of diverse matrices. For that reason, many studies that utilize the spatial econometrics models have applied multiple spatial weight matrices in their empirical applications (Dubin, 1988; Can, 1992). To identify the most effective spatial weight matrix, the present study adopts contiguity matrix, inverse distance matrix, and inverse distance weight matrix. The weight matrixes were row-standardized to avoid some probable scale effects.

(2) GWR, Mixed GWR

Geographically Weighted Regression (GWR) allows us to identify the local effects of independent variables on crimes for each area. Following Brunsdon et al. (1999), GWR estimates parameters to differ in values depending on the spatial location, not having same values in all over the target areas. GWR is mathematically expressed as Eq. (7).

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{m}\beta_k(u_i,v_i)x_{ik} + \epsilon_i,\ i = 1,2,\cdots,n \qquad \text{Eq.(7)}$$

y_i : i th dependent variable

(u_i,v_i) : location in the studied geographical region

β_0 : coefficient of intercept

β_{ik} : coefficients of independent variables

x_{ik} : independent variables

ϵ_i : error term ($\epsilon_i \sim N(0,\sigma_\epsilon^2)$)

When Eq. (7) is converted to a matrix, parameters can be estimated using the following Eq. (8).

$$\hat{\beta}(u_i,v_i) = [X^T W(u_i,v_i)X]^{-1} X^T W(u_i,v_i)\,Y \qquad \text{Eq.(8)}$$

where $W(u_i,v_i)$ is a spatial weight matrix. There are diverse spatial weight matrixes that can be applied to GWR models such as Bi-square, Tri-cube and Gaussian. The present study adopts exponential weight.

The GWR model in Eq. (7) also can be converted to Eq. (9), a mixed GWR model suggested by Brunsdon et al. (1996).

$$y_i = \beta_0(u_i,v_i) + \sum_{k=1}^{l}\beta_k x_{ik} + \sum_{k=l+1}^{m}\beta_{1k}(u_i,v_i)x_{ik} + \epsilon_i \qquad \text{Eq.(9)}$$

where $\beta_k(1,\cdots,l)$ represents a global parameter and $\beta_k(l+1,\cdots,m)$ refers to a local parameter. Eq. (10) is a matrix converted from Eq. (9).

$$Y = X_G\beta_G + m + \epsilon, \quad m = \sum_{k=l+1}^{m} \beta_{ik}(u_i, v_i)x_{ik} \qquad \text{Eq.(10)}$$

When the global parameter β_G is known as in Eq. (10), the local parameter m can be estimated using Eq. (11).

$$\hat{m} = L(Y - X_G\beta_G),$$
$$L = \begin{pmatrix} X_1^T[X^T W(u_1,v_1)X]^{-1}X^T W(u_1,v_1) \\ X_2^T[X^T W(u_2,v_2)X]^{-1}X^T W(u_2,v_2) \\ \vdots \\ X_n^T[X^T W(u_n,v_n)X]^{-1}X^T W(u_n,v_n) \end{pmatrix} \qquad \text{Eq.(11)}$$

Whether the parameter $\beta_k(u_i,v_i)$ in Eq. (7) is identified as local or global can be determined using F-test which was suggested by Mei et al. (2004).

(3) Local Spatial Cluster Detection Methods

As for the independent variables which are ascertained as local parameters by the MGWR model, the parameters can be clustered so that the local characteristics and differences can be more easily derived. In order to do so, the present study adopts Local Getis and Ord's G (Getis and Ord, 1992). To apply Local Moran's I and Local Getis and Ord's G, it is very important to define spatial weight matrix that represents the spatial proximity between areas. While the types of spatial weight matrix vary, the present study adopts an inverse distance matrix.

2. Data and Variables

The analysis of crime incidence in Korea is as of 2005. Although it is reasonable to use more recent data or to conduct a dynamic time-series analysis from past to the present, relevant data is not accessible or available when the study was conducted. The geographical boundary of police district is not consistent with that of the administrative boundary that may lead to geographical inconsistency between the number of crime incidences by police precincts and independent variables from the census data. To correct this inconsistency, the present study manually discovers and fixes geographical boundary of independent variables to have them tuned to the lower level local autonomy (Gun and Gu).

All the variables adopted in this study are selected with regard to the theoretical and empirical validity supported by previous studies and the availability of relevant data. The crime incidence data are standardized by areal population to represent the number of total crime per ten thousand persons. Independent variables consist of socio-economic and spatial planning variables. Socio-economic variables are residential stability, number of divorcee, youth population, population of the highly educated, number of beneficiaries of basic livelihood security, residential stability, per capita local tax, and number of policemen. Spatial planning variables are residential concentration, mixed land use, concentration of crime prevention facilities, and spatial accessibility. Residential stability, number of divorcee, number of beneficiaries of basic livelihood security, and per capita local tax are derived from aggregated statistics by Statistics Korea, an official government agency. We extract such variables as youth population, population of the college educated, and residential stability from the 2% Population and Housing Micro Data by the same agency. Information about number of policemen is derived from an internal data set of National Police Agency in Korea.

Tab. 2 Descriptive Statistics and Description of Variables

Variables		Description of variables	Mean	Standard Deviation
<Dependent Variable>				
Crime Incidence		Total crime incidence per ten thousand inhabitants	384.80	169.83
<Independent Variable>				
Socio-Economic	Number of inhabitants	Number of inhabitants in police precinct (persons)	364,994	179,512
	Number of divorcee	Per one thousand population	2.70	0.79
	Youth population	(Population of youth in age fifteen to twenty-four / total population)×100(%)	14.19	1.79
	Population of the highly educated	(Population of college graduates / total population)×100(%)	29.00	7.81
	Number of beneficiaries of basic livelihood security	Number of households under national basic livelihood security / total number of households (%)	2.13	1.26
	Residential stability	Number of households that have lived in a region for more than five years / total number of households (%)	71.68	7.21
	Per capita local tax	Total sum of local tax / total population (KRW)	2,311,564	1,879,861
	Number of policemen	Number of policemen / one thousand population	1.79	0.88
Spatial Planning	Residential concentration	The level of spatial concentration of residential areas	0.19	0.12
	Mixed land use	The extent to which urban land uses (residential, commercial, industrial, public facilities, amusement facilities) are mixed	0.08	0.05
	Concentration of crime prevention facilities	The level of spatial concentration of crime prevention areas	0.12	0.12
	Spatial accessibility	Least travel time by regions (minutes)	141.81	11.40

Spatial planning variables are mostly constructed from the GIS processing, especially through macroscopic spatial analyses. Residential concentration and concentration of crime prevention facilities are calculated using the same method, but the spatial data extraction methods are different from each other. To construct the variable of residential concentration, residential areas are retrieved from a vector of land cover map issued by Ministry of Environment in Korea. The retrieved residential areas, polygon data, are then converted to point data to conduct a point-based spatial analysis. As for concentration of crime prevention facilities, police stations and boxes (polygon) are extracted from Architectural Information System, and then converted to point data. The point data for residential area and police stations/boxes are analyzed using Kernel Density Function, a sort of spatial interpolation methods. Finally, average value of each variable is calculated by police precincts.

In estimating the level of mixed land use, entropy index has been widely adopted. The index, however, only identifies the extent to which land uses are mixed while not considering the extent of spatial connectivity based on spatial locations. The present study constructs mixed land use utilizing dissimilarity index proposed by Cervero and Kockelman (1997) to reflect the spatial connectivity between land uses. Dissimilarity index explains how much the land use in the center of three by three grids differs from the surrounding eight grids, which can be expressed as Eq. (12).

$$\text{Dissimilarity Index} = \sum_k \frac{1}{k} \sum_i^8 \frac{X_{ik}}{8} \qquad \text{Eq.(12)}$$

where k represents the size of an unit grid. X_{ik} is 0 when the land use is identical to that of adjacent grids and 1 when it is not. This means that the mixed land use has a value ranging from 0 to 1. To prepare mixed land use, established areas are first extracted from land cover maps issued by Ministry of Environment and then converted to 20m by 20m grids format. Based on the data, dissimilarity index is computed using the Focal Statistics option of ArcGIS 10.0 and the averages values are computed by police precincts. Spatial accessibility is based on the least travel time issued by the Korea Transport Institute. The least travel time refers to a travel time from one traffic zone to all the other zones (161 zones in total).

We construct ex-ante assumptions regarding the impacts of the independent variables on crime incidence. Among the socio-economic variables, number of inhabitants in a region may have most direct impacts on crime incidents, assuming the variable is likely to have a positive effect on crime incidence. According to social disorganization theories, the increase in family dissolution caused by divorcee may lead to high crime rates (Smith et al., 2000). Some studies found that family disorganizations due to divorcee cause crime incidence (Sampson, 1985; Smith et al., 2000; Lee and Lee, 2009; Cheong and Park, 2010). In this context, the number of divorcee is likely to be positively correlated with crime incidence. Crimes in Korea as well as western societies have been most frequently committed by younger age group (Ko, 2001). This implies that regions with higher youth population are likely to have higher chance of crimes. Those who have low level of education tend to be less adaptable to society. Accordingly, higher proportion of highly educated people in a region is likely to be associated negatively with crime incidence. People who pay higher per capita property tax tend to have higher educational background and live in areas with more security facilities. This allows us to expect that per capita local tax has negative impacts on crime (Lee and Cho, 2006). Loosing social ties undermines the informal control power of local community, weakening natural surveillance by community members so that the crimes can be more easily committed (Bottoms and Wiles, 1992). Residential stability, a criterion of social bond is thus likely to reduce the crime rates. The more the number of policemen exposes in an area, the less the crime incidence is expected since one of the major roles of policemen is to prevent crime.

Residential concentration is likely to be positively associated with crime incidence since people residing in concentrated residential areas tend to have difficulties in mingling with neighbors and community members as explained by social disorganization theory. Routine activity theory also insists that the higher residential concentration increases the opportunity of crimes. Concentration of crime prevention facilities will help suppress crime incidence. Areas with mixed land use tend to have more floating population, which implies that more opportunity of crimes along with less natural surveillance (Taylor et al., 1995). However, some researchers have insisted that mixed land use can rather reduce crime incidents by increasing potential surveillance capability (Grant, 2002). As there have been only a few empirical studies carried out on the relevant issue so far, it is difficult to assure which perspective is more prevalent. The present study takes both theories into consideration to reach which one is more persuasive in Korea's circumstances.

Spatial accessibility can both positively and negatively affect crime incidence. Higher spatial accessibility either allows criminals to escape quickly (Johnston and Bowers, 2010) or facilitates crime prevention activities such as police patrol (Cozens and Love, 2009).

4 Results

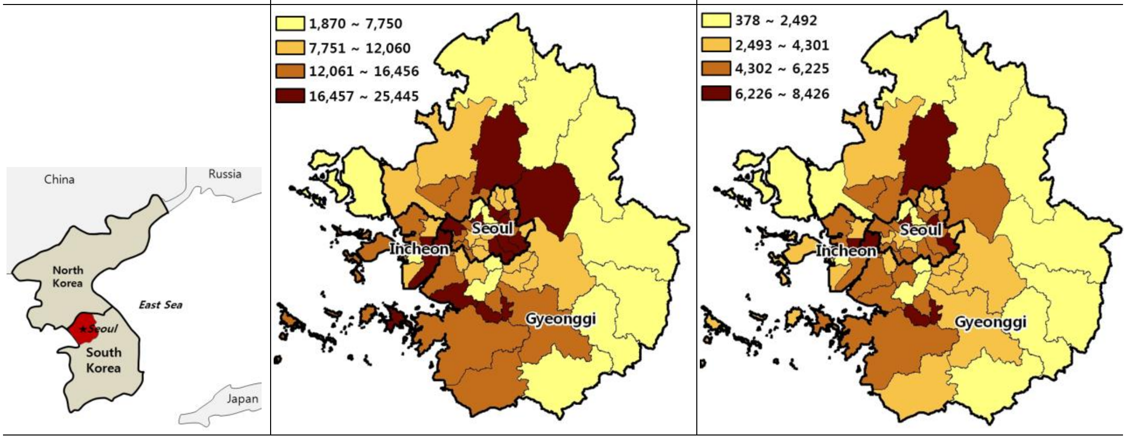
1. Crime Incidences in SMA

According to a survey carried out by Statistics Korea (2012), 29.3 percent of Korean thinks that crime is the most influencing factor to threatening their social security. According to a series of internal data of Korea's National Police Agency, there have been approximately 180 million crimes per annum over the past 10 years (from 2001 to 2010) in Korea. The total number of crimes in 2001 was 1,829,229 and slightly decreased to 1,735,711 in 2010 with average number of crime incidents at 1,827,181 by annum during the periods. However, the sum of five major crimes (murder, robbery, rape, theft, and violence) had increased by 10.2 percent during the period from 530,636 to 584,655. In general, the total number of crimes has been maintained steadily with slight fluctuations, but the sum of five crimes has significantly been increased during the last ten years. This shows a tendency that the crime in Korea has became more brutal as time passes by.

The crime rates vary by region in Korea. As of 2005, the largest number of crime was occurred in Seoul Metropolitan Area where almost 48.2 percent of the population resides. About 46.2 percent of total crime in Korea (788,303 cases) and 51.1 percent of five major crimes (256,873 cases) occurred in SMA. <Figure 1> presents geographical distribution of total crimes and five major crimes of SMA as of 2005. In general, the farther the location is from the center of SMA, the less the crime rate is. This geographical tendency probably stems from the huge difference in population between the suburban areas and Seoul Metropolitan City. Since no significant difference for the prevalence between total crime and five major crimes among regions in SMA, further investigation will be conducted focusing mainly on total crime.

Fig. 1 Crime Occurrence by regions in SMA (2005)

Location of SMA	Total Crime	Five Major Crimes



2. Determinants of Crime Victimization

The determinants of crime incidence of SMA are analyzed with double logarithmic transformation. <Tables 3> show the regression results. As previously discussed, there prepared three spatial weighted matrixes to apply SAR, SEM, and SAC models. We found that the spatial contiguity matrix shows the highest explanatory power. Therefore, the present study interprets the results based on the application of the adjacency matrix. We include additional results with inverse distance matrix and inverse distance weighted matrix in <Appendix 1> for readers' discretion.

Table 3 shows that SAC model has the highest explanatory power among the models. Also the rho and lambda, which reflects the spatial dependence and spatial autocorrelation, are statistically significant in the SAC model. Therefore the present study interprets the regression results based mainly on the SAC model. As the present study adopts the double logarithmic transformations, the estimated coefficients can be interpreted as their elasticity. The results show how the elasticity on total crime changes by any one percent increase of independent variables. The impacts of independent variables on crimes in SMA generally matched with our expectation, although some of them are deviated from the hypotheses.

While marginally significant at p<.10, number of inhabitants is positively associated with crime incidence. As expected by the social disorganization theory, breakdown of families can lead to high level of crime incidence. This theory gains ground in SMA as the number of divorcees has a positive effect on crime incidence, that is, one percent increase of divorcee in a region may cause 0.13% increase of total crime. Taxation and distribution of policemen prove to be significant determinants for total crime at p<.01. Per capita local tax shows a positive impact on crime incidence. One percent increase of local tax may reach 0.11% increase of total crime. In the same line of reasoning, number of beneficiaries of basic livelihood security is negatively associated to crime incidence in four models. The coefficients of OLS, SAR, SEM are statistically significant at p<.01 and p<.10, although the coefficient of SAC is not in the traditionally acceptable significance level. Since taxation and number of beneficiaries of basic livelihood security in an area are closely related to the level of livelihood, this may imply that the affluent areas are likely to have more crimes and less crime incidence in poor regions in SMA. The finding is somewhat deviated from that of the previous studies from western societies that report crime is prevalent in poor neighborhoods (Edmark, 2005, Hope, 2001, Hope et al., 2001). However, the findings are matched with those from other countries (McCall and Nieuwbeerta, 2007, Patterson, 1991, Pridemore, 2008).

Contrary to the hypothesis, the number of policemen positively affects crimes. One percent increase of policemen in an area can cause the increase of the total crime rate by 0.79% and the impact is by far the highest one among the twelve covariates of our model to determine total crime incidence in SMA. The result implies that the current deployment of policemen is not effective at all in preventing crimes, requiring an immediate redistribution of the policemen in SMA. Other independent variables - youth population, population of the highly educated, number of beneficiaries of basic livelihood security and residential stability – are turned to be statistically insignificant, which means they are not likely to have direct impacts on crime incidence in SMA.

Tab. 3 Regression Results of Total Crime, SAR, SEM, SAC

Variable	OLS	SAR	SEM	SAC	VIF
Intercept	3.8028	9.5083 **	3.8654	28.1211 ***	
<u>Socio-Economic Variable</u>					
Settled population	0.0505	0.0453	0.0899	0.1255 *	6.19
Number of divorcee	0.3372 ***	0.3187 ***	0.2918 ***	0.1249 *	1.87
Youth population	0.2041	0.2030	0.1833	0.0217	3.92
Population of the highly educated	-0.0079	-0.0045	0.0160	0.1037	5.00
Number of beneficiaries of basic livelihood security	-0.1499 **	-0.1528 **	-0.1147 *	-0.0293	2.58
Residential stability	-0.2327	-0.1982	-0.2859	-0.3356	2.67
Per capita local tax	0.0852 *	0.0916 **	0.0896 **	0.1101 ***	2.25
Number of policemen	0.7076 ***	0.6842 ***	0.7796 ***	0.7873 ***	3.83
<u>Spatial Planning Variable</u>					
Residential concentration	-0.2733 **	-0.2681 ***	-0.2686 ***	-0.1890 ***	9.81
Mixed land use	0.3201 ***	0.3216 ***	0.3123 ***	0.2691 ***	5.28
Concentration of crime prevention facilities	-0.0707	-0.0718 **	-0.0724 *	-0.0574 *	6.79

Spatial accessibility	0.2151	0.2242	0.1353	0.0739	1.91
rho		-0.9940		-0.9034 ***	
lambda			0.7670 ***	0.7086 ***	
N	63	63	63	63	
R-Square	0.7883	0.8129	0.8086	0.8799	
Adj R-Square	0.7375	0.7681	0.7627	0.8510	

*: p<0.1, **: p<0.05, ***: p<0.01

When turning to the effects of the spatial planning variables on total crime incidence, we find three out of four variables are in the range of the designated significance level. Residential concentration and concentration of crime prevention facility seem to have negative effects on total crime incidence. One percent increase of residential concentration results in 0.19% increase of total crime and the effect of crime prevention facilities on total crime shows 0.06%. This is probably because the increased density of residential areas and crime prevention facilities reinforces the natural surveillance capability which in turn deters crime. One percent increase of mixed land use boils down to 0.27% increase on total crime incidence to areas. We suspect that various land uses lead to more floating population and increase the crime opportunities by offenders while undermining natural surveillance capability. It is natural because mixed land use is common in commercial centers where chances of crime occurrence are higher. Spatial accessibility is not statistically significant, which implies accessibility condition of areas has no direct causal relationship with crime incidence in SMA[1].

It is notable that the magnitude and statistical significance of spatial planning variables is relatively more important when compared to those of socio-economic variables. This implies that effective spatial planning practices can reduce total crime incidence in SMA. In light of these findings, we believe it is urgent to prepare spatial planning strategies to prevent crime for SMA, particularly for the redistribution of police deployment.

Table 4 shows the direct effect, indirect or spillover effect, and total effect of independent variables on total crime incidence. We apply Eq. (6) to analyze the estimation results of the statistically significant variables in the SAC model. Statistically significant variables are number of inhabitants, per capita local tax, the number of policemen, residential concentration, mixed land use, and concentration of crime prevention facility. Note that these direct effect estimates are different from the coefficient estimates reported in <Table 3> due to feedback effects that arise as a result of impacts passing through neighboring local autonomies and back to the autonomies themselves.

Variables showing the highest direct effect and indirect effect are the number of policemen, which is followed by mixed land use, residential concentration, number of inhabitants, per capita local tax, and concentration of crime prevention facility. In all the variables, indirect or spatial spillover effect is smaller than the direct effect, which makes sense since the impact of a change will most likely be larger in the area that triggered the change.

---

[1] There is a possibility that the impact of the variable on crime incidence is overlapped with that of other spatial planning variables like mixed land use and residential concentration since those variables are quite relevant to the level of accessibility.

For these variables, the direct effects are opposite to the direct effects in their sign (positive and negative). Variables whose direct effects have positive sign are settled population, per capita local tax, and mixed land use, while ones with negative direct effects are residential concentration and concentration of crime prevention facilities. In order to prevent crime more efficiently, it is highly required to manage both direct and indirect effects of a criminogenic environment. As the direct and indirect effects of spatial planning variables are not negligible, it is necessary to reinforce spatial planning strategies for crime prevention. The findings of the present study expect to provide fundamental information for future crime prevention strategies for SMA.

Tab. 4 Direct, Indirect and Total Effects of Independent Variables on Crime Incidence

Variable	Direct effect	Indirect effect	Total effect
Socio-Economic Variable			
Settled population	0.1480 *	-0.0426 *	0.1054 *
Number of divorcee	0.1481	-0.0389	0.1092
Youth population	0.1920	-0.0592	0.1327
Population of the highly educated	-0.0523	0.0190	-0.0333
Number of beneficiaries of basic livelihood security	-0.0628	0.0184	-0.0444
Residential stability	-0.4468	0.1291	-0.3177
Per capita local tax	0.1260 ***	-0.0365 *	0.0894 ***
Number of policemen	0.8508 ***	-0.2423 **	0.6085 ***
Spatial Planning Variable			
Residential concentration	-0.2427 ***	0.0691 *	-0.1736 **
Mixed land use	0.3341 ***	-0.0952 **	0.2389 ***
Concentration of crime prevention facilities	-0.0900 **	0.0255 *	-0.0646 **
Spatial accessibility	0.1707	-0.0577	0.1129

Notes
Applied estimation results of SAC based on adjacency matrix.
*: p<0.1, **: p<0.05, ***: p<0.01

Table 5 represents crime determinants derived from GWR and MGWR. Here we discuss the results focusing on MGWR. According to the estimation results from MGWR, independent variables proved as local parameters are number of divorcees and number of policemen while all the other variables are confirmed as global parameter at five percent significance interval. <Figure 3> depicts the two independent variables proved as local parameters and the clusters of the parameters. Clustering the local parameters allows us to identify the regional disparity of the crime incidence by the two independent variables. Local Getis and Ord's G is adopted for the clustering and the clusters are schematized at five percent significance interval.

Tab. 5 Regression Results of Total Crime in GWR, MGWR

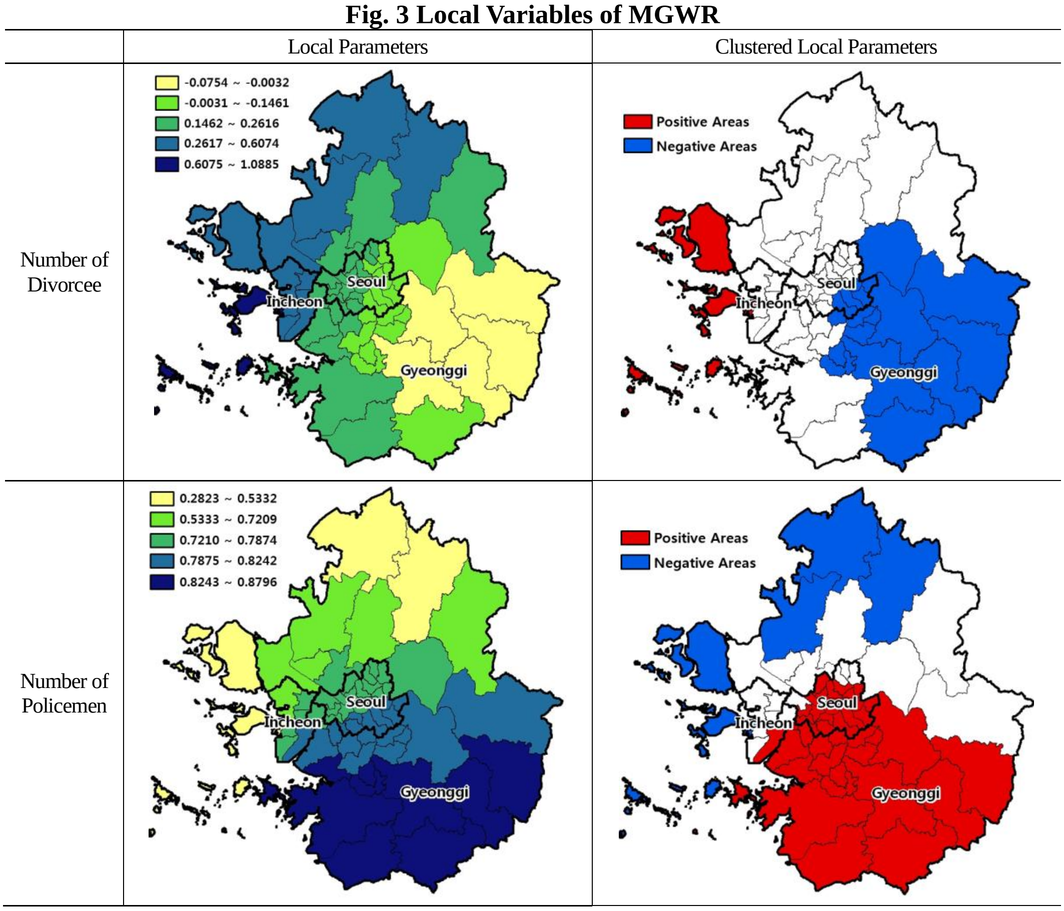
Variable	GWR	MGWR		
			p-value	Local Parameter
Intercept	1.7219 L	-0.0078	0.1461	
Socio-Economic Variable				
Settled population	0.0329 L	0.0829	0.9332	
Number of divorcee	0.2383 L	0.1912	0.0004	Local
Youth population	0.5771 L	0.5719 *	0.8246	
Population of the highly educated	-0.1378 L	-0.2638	0.3778	
Number of beneficiaries of basic livelihood security	-0.1064 L	-0.1280 **	0.3401	

Residential stability	-0.6349 L	-0.3854	0.9056	
Per capita local tax	0.1136 L	0.7648	0.0793	
Number of policemen	0.7245 L	0.1255	0.0391	Local
Spatial Planning Variable				
Residential concentration	-0.2109 L	-0.2154 **	0.1274	
Mixed land use	0.2678 L	0.2171 **	0.1138	
Concentration of crime prevention facilities	-0.0764 L	-0.0679 **	1.0000	
Spatial accessibility	0.8912 L	0.9566 ***	0.1284	
N	63	63		
R-Square	0.8713	0.8083		
Adj R-Square	0.8405	0.7623		
Decay Type	exponential	exponential		

L: Refers to a local coefficient based on the average of local coefficients
*: p<0.1, **: p<0.05, ***: p<0.01

The impacts of independent variables that are proved as local parameters show a stark difference by areas. As for number of divorcees, areas with positive effects on crimes are clustered in the northwestern SMA, while areas with negative effects are in southeastern SMA. The local parameters of number of policemen show positive impacts on crimes in every area. The impact is noticeably high in the center of SMA and relatively low in southern SMA. Since the crime prevention strategies should be based on the locality of the region, the clustering analysis can provide fundamental information to reflect the local characteristics of SMA that are suitable for crime prevention strategies.

Fig. 3 Local Variables of MGWR



5 Conclusions

Crime has everything to do with spaces. So, it is very important how to control the spatial dependency when studying crimes. The present study has explored the impacts of spatial planning factors on crime incidence in SMA. To consider the spatial dependency of crime incidence, the present study adopts diverse spatial econometrics models and three types of spatial weighted matrices. Spatial planning variables adopted in the present study are residential concentration, mixed land use, concentration of crime prevention facilities, and spatial accessibility. The present study suggests the followings for the spatial planning strategies to prevent crime.

As residential concentration seems effective in reducing or deterring crimes, it is recommended to maintain the residential concentration at a certain level. Therefore, further studies should be followed to identify a reasonable residential density, as residential density has a close relationship with the quality of residential environment.

Mixed land use works positively on crime incidence. This is probably because mixed land use leads to increased floating population where people become more likely to get exposed to crimes. Modern theories in urban planning such as compact city and new urbanism tend to encourage mixed use of land developments. As the mixed use developments seem to increase crimes, it is recommended to change to a lower level.

Concentration of crime prevention facilities has positive effects on reducing crimes. So it is recommended to increase the spatial distribution of the facilities. As the concentration of crime facility is determined by the location and size of the relevant facilities, location plans of the facilities should be established based on comprehensive investigations. Spatial accessibility showed a positive effect on crime occurrence. Further discussions are required to establish the appropriate level of spatial accessibility for crime prevention.

It is a common knowledge that the spatial variables adopted in the present study are fundamental components of spatial planning and that can be utilized to establish comprehensive urban master plans. An urban master plan in Korea is superior to any other spatial plans legally established by any municipality. It determines fundamental frameworks including land use and location of facilities through planning processes. It is undeniable that urban master plans in Korea have rarely dealt with fundamental crime issues. Even though they save some sections for disaster prevention plans, those partial plans that mainly focus on natural disaster prevention strategies are not enough. Moreover, as the impacts of spatial planning on crime are expected to differ by regions, region-wide efforts, awareness, and participation should be encouraged to establish participatory and effective crime prevention measures.

Due to the absence of time-series data on the spatial variables, the present study has not carried out a dynamic analysis to identify determinants of crime incidence. Although we identified the relationship between spatial planning factors and crime incidence at one point in time, further studies on this relationship that examines a longitudinal perspective are also needed, especially with reference to the factors that have not been adopted in the present study including urban planning facilities, zones, areas and districts. In addition, such studies will be based on microscopic data, rather than aggregated data, so that the relationship between more detailed microscopic characteristics of spaces and crimes can be identified.

References

Andresen, M. A., 2006, Crime Measures and the Spatial Analysis of Criminal Activity, *British Journal of Criminology*, 46(2): 258-285.

Anselin, L., 1988, *Spatial Econometrics : Method and Models, Dordrecht*: Kluwer Academic.

Anselin, L., 2002, Under the Hood: Issues in the Specification and Interpretation of Spatial Regression Models, *Agricultural Economics*, 27(3): 247-267.

Baller, R., Anselin, L., Messner, S., Deane, G. and Hawkins, D., 2001, Structural Covariates of US County Homicide Rates: Incorporating Spatial Effects, *Criminology*, 39(3): 561-590.

Barnet, C. and Mencken, F. C., 2002, Social Disorganization Theory and the Contextual Nature of Crime in Nonmetropolitan Counties, *Rural Sociology*, 67(3): 372-393.

Becker, G. S., 1968, Crime and Punishment: An Economic Approach, *The Journal of Political Economy,* 76(2): 169-217.

Blau, J. R. and Blau, P. M., 1982, The Cost of Inequality: Metropolitan Structure and Violent Crime, *American Sociological Review*, 47(1): 114-129.

Bottoms, A. and Wiles, P., 1992, Explanations of Crime and Place, in Evans, D. J., Fyfe, N. R. and Herbert, D. T.(eds.), Crime, *Policing and Place, London*: Routledge.

Browning, C. R., Byron. R. A., Calder, C. A., Krivo, L. J., Kwan, M. P., Lee, J. Y. and Peterson, R. D., 2010, Commercial, Density, Residential, Concentration, and Crime : Land Use Patterns and Violence in Neighborhood Context, *Journal of Research in Crime and Delinquency*, 47(3): 329-357.

Brunsdon, C., Fotheringham, A. S. and Charlton, M., 1999, Some Notes on Parametric Significance Tests for Geographically Weighted Regression, *Journal of Regional Science*, 39(3): 497-524.

Buonanno, P., 2006, *The Socioeconomic Determinants of Crime: A Review of the Literature*. Working Paper No 63. Department of Economics, University of Milan-Bicocca.

Cahill, M. and Mulligan, G., 2007, Using Geographically Weighted Regression to Explore Local Crime Patterns, *Social Science Computer Review*, 25(2): 174-193.

Can, A., 1992, Specification and Estimation of Hedonic Housing Price Model, *Regional Science and Urban Economics*, 22(3): 453-473.

Ceccato, V., Haining, R. and Signoretta, P., 2002, Exploring Offence Statistics in Stockholm City Using Spatial Analysis Tools, *Annals of the Association of American Geographers*, 92(1): 29-51.

Cervero, R. and Kockelman, K., 1997, Travel Demand and the Three 3Ds: Density, *Diversity and Design, Transportation Research Part D*, 2(3): 199-219.

Chang, D. K., 2009, Social Crime or Spatial Crime? Exploring the Effects of Social Economical, and Spatial Factors on Burglary Rates, *Environment and Behavior*, 43(1): 26-52.

Chapin, D., 1991, Making Green Places Safer Places: Experiences in New York City, Landscape *Architecture Review*, 12(3): 16-18.

Cheong, J. S. and Park, H. H., 2010, A Study on the Effects of Structural Covariates on Homicide: Nationwide Analysis Using Negative Binomial Regression Model, *Korean Criminological Review*, 21(1): 91-119.

Chun, Y. W. and Park, Y. H., 2008, Neighborhood Effects and Spatial Patterns in Urban Crime: A Case Study of the City of Dallas, Texas, *Journal of the Korean Urban Geographical Society*, 11(1): 85-99.

Clinard, M. B., 1978, *Cities without Crime: the Case of Switzerland, London*: Cambridge University Press.

Cohen, L. E. and Felson, M., 1979, Social Change and Crime Rate Trends: A Routine Activity Approach, *American Sociological Review*, 44(4): 588-608.

Corman, H. and Mocan, H. N., 2005, Carrots, Sticks and Broken Windows, *Journal of Law and Economics*, 48(1): 235-266.

Cozens, P. and Love, T., 2009, Manipulating Permeability as a Process for Controlling Crime: Balancing Security and Sustainability in Local Contexts. *Built Environment*, 35(1): 346-365.

Dubin, R. A., 1988, Estimation of Regression Coefficients in the Presence of Spatially Autocorrelated Error Terms, *The Review of Economics and Statistics*, 70(3): 466-474.

Eck, J. E. and Weisburd, D., 1995, *Crime and Place, Crime Prevention Studies 4, New York*: Willow Tree Press.

Getis, A. and J. K. Ord., 1992, The Analysis of Spatial Association by Use of Distance Statistics, *Geographical Analysis*, 24(3): 189-206.

Goudriaan, H., Wittebrood, K. and Nieuwbeerta, P., 2006, Neighbourhood Characteristics and Reporting Crime, *British Journal of Criminology*, 46(4): 719-742.

Grant, J., 2002, Mixed Use in Theory and Practice: Canadian Experience with Implementing a Planning Principle, *Journal of the American Planning Association*, 68(1): 71-84.

Herbert, D., 1982, *The Geography of Urban Crime, London*: Longman.

Hilbron, J., 2009, *Dealing with Crime and Disorder in Urban Parks, Center for Problem-Oriented Policing*, Washington, D.C.

Hiller, B. and Shu, S., 2000, Crime and Urban Layout: The Need for Evidence, In: Ballintyne S, Pease K, McLaren V (eds) Key Issues in Crime Prevention, *Crime Reduction and Community Safety*. IPPR, London.

Hipp, J. R., 2007, Block, Track, and Levels of Aggregation: Neighborhood Structure and Crime and Disorder as a Case in Point, *American Sociological Association*, 72(5): 659-680.

Hooghe, M., Vanhoutte, B., Hardyns, W. and Bircan, T., 2011, Unemployment, Inequality, Poverty and Crime: Spatial Distribution Patterns of Criminal Acts in Belgium, 2001–06, *British Journal of Criminology*, 51(1): 1-20.

Johnston, S. and Bowers, K., 2010, Permeability and Burglary Risk: Are Cul-de-sacs Safer?, *Quantitative Journal of Criminology*, 26(1): 89-111.

Ko, J. H., 2001, Crime Patterns of CBD in Cheongju City, *Journal of the Korean Geographical Society*, 36(3): 329-341.

Lee, D. S. and Lee, K, H., 2009 A Study on the Relationship Between Crime Rates and Characteristics of Urban Areas : Focusing on Demographic and Socio-Economic Factors, *Natioanal Association Korean Local Government Studies*, 11(1): 189-206.

Lee, S. W. and Cho, J. K., 2006, The Effects of Spatial and Environmental Factors on Crime Victimization, *Seoul Studies*, 7(2): 57-76.

LeSage, J. P. and Pace, R. K., 2009, *Introduction to Spatial Econometrics, Boca Raton*: CRC

Press/Taylor & Francis.

Lesage, J. P., 1999, *The Theory and Practice of Spatial Econometrics*, Available: http://www.spatial-econometrics.com/html/sbook.

Lockwood, D., 2007, Mapping Crime in Savannah: Social Disadvantage, Land Use, and Violent Crimes Reported to the Police, *Social Science Computer Review*, 25(2): 194-209.

Mei, C. L., He, S. Y. and Fang, K. T., 2004, A Note on the Mixed Geographically Weighted Regression Model, *Journal of Regional Science*, 44(1): 143-157.

Mocan, H. N. and Rees, D. I., 2005, Economic Conditions, Deterrence and Juvenile Crime: Evidence from Micro Data, *American Law and Economics Review*, 7(2): 319-349.

Morenoff, J. D., Sampson, R. J. and Raudenbush, S. W., 2001, Neighborhood Inequality, Collective Efficacy, and the Spatial Dynamics of Urban Violence, *Criminology* 39(3): 517-559.

Newman, O., 1973, *Defensible Space: Crime Prevention Through Urban Design, New York*: McMillan.

Novak, K. and Seiler, C., 2001, Zoning Practices and Neighborhood Physical Disorder, Criminal *Justice Policy Review*, 12(2): 140-163.

Paulsen, D. J. and Robinson, M. B., 2004, *Spatial Aspects of Crime: Theory and Practice, Boston*: Rearson Education, Inc.

Paulsen, D., 2011, *Designing Out Crime: What Works and What doesn't, NIJ MAPS* Annual Conference, Miami.

Petee, T. A. and Kowalski, G. S., 1993, Modeling Rural Violent Crime Rates: A Test of Social Disorganization Theory, *Sociological Focus*, 26(1): 87-89.

Petee, T. A., Kowalski, G. S. and Duffield, D. W., 1994, Crime, Social Disorganization, and Social Structure: A Research Note on the Use of Interurban Ecological Models, *American Journal of Criminal Justi*ce, 19(1): 117-132.

Sampson, R. J. and Groves, W. B., 1989, Community Structure and Crime: Testing Social-Disorganization Theory, *The America Journal of Sociology*, 94(4): 774-802

Sampson, R. J. and John, D. W., 1987, Linking the Micro-Level and Macro-Level Dimensions of Lifestyle-Routine Activity and Opportunity Models of Predatory Victimization, American *Journal of Sociology*, 3(4): 371-393.

Sampson, R. J., 1985, Neighborhood and Crime: The Structural Determinants of Personal Victimization, *Journal of Research in Crime and Delinquency*, 22(1): 7-40.

Shaw, C. R. and Mckay, H. D., 1942, *Juvenile Delinquency and Urban Areas, Chicago*: University of Chicago Press.

Smith, W. R., Frazee, S. G. and Davison, E. L., 2000, Furthering the Integration of Routine Activity and Social Disorganization Theories: Small Units of Analysis and the Study of Street Robbery as a Diffusion Process, *Criminology*, 38(2): 489-523.

Statistics Korea, 2012, Social Indicators in Korea.

Stucky, T. D. and Ottensmann, J. R., 2009, Land Use and Violent Crime, *Criminology* 47(4): 1223-1264.

Taylor, R. B., Barbara, A. K., Ellen, M. K., Jack, R. G. and Douglas, D. P., 1995, Street Blocks with More Nonresidential Land Use Have More Physical Deterioration: Evidence from

Baltimore and Philadelphia, *Urban Affairs Review*, 31(1): 120-136.

Warner, B. D. and Pierce, G. L., 1993, Reexamining Social Disorganization Theory using Calls to the Police as a Measure of Crime, *Criminology*, 31(4): 493-517.

Witt, R., Clarke, A. and Fielding, N., 1999, Crime and Economic Activity: a Panel Data Approach, British *Journal of Criminology*, 39(3): 391-400.

Yoon, O. K. and Joo, H. J., 2005, A Contextual Analysis of Crime Rates: The Korean Case, Crime, *Law & Social Change*, 43(1): 31-55.

Appendix 1 Comparison of Regression Results from SAR, SEM, SAC by the Type of Spatial weighted Matrix Applied

Variable	inverse distance matrix			inverse distance weighted matrix		
	SAR	SEM	SAC	SAR	SEM	SAC
Intercept	9.1719	6.5111	41.2743 ***	7.1493	6.6592	9.4295 **
Socio-Economic Variable						
Settled population	0.0290	0.0925	0.1088	0.0353	0.1573	0.1470
Number of divorcee	0.2551 *	0.2024	0.0245	0.2569 *	0.1213	0.1084
Youth population	0.2452	0.2674	0.0551	0.2541	0.2588	0.2126
Population of the highly educated	-0.2692	-0.2479	-0.0640	-0.2748	-0.2007	-0.1849
Number of beneficiaries of basic livelihood security	-0.1319	-0.0865	0.0031	-0.1297	-0.0290	-0.0278
Residential stability	-0.3508	-0.4085	-0.3926	-0.3585	-0.5056	-0.4896
Per capita local tax	0.0850	0.0901	0.0945 **	0.0852	0.0995 *	0.1046 *
Number of policemen	0.5891 ***	0.7041 ***	0.6420 ***	0.6037 ***	0.8234 ***	0.8000 ***
Spatial Planning Variable						
Residential concentration	-0.1691	-0.1825	-0.0790	-0.1719	-0.2074 *	-0.1834
Mixed land use	0.3352 **	0.3221 **	0.2710 ***	0.3347 **	0.3076 **	0.3108 **
Concentration of crime prevention facilities	-0.0337	-0.0333	0.0000	-0.0357	-0.0154	-0.0161
Spatial accessibility	-0.2403	-0.3178	-0.3668	-0.2378	-0.4644	-0.4607
rho	-0.4740		-0.2910	-0.0660		-0.5390
lambda		0.7390 ***	0.7999 ***		0.8260 ***	0.8850 ***
N	63	63	63	63	63	63
R-Square	0.6200	0.6308	0.7016	0.6081	0.6825	0.7025
Adj R-Square	0.5288	0.5422	0.6416	0.5140	0.6063	0.6311

* p<0.1, ** p<0.05, *** p<0.01