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Original article

Exploring Spatial Patterns of Theft Crimes Using Geographically Weighted Regression

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Abstract

The goal of this study was to efficiently analyze the relationships of the number of thefts with related factors, considering the spatial patterns of theft crimes. Theft crime data for a 5-year period (2009–2013) were collected from Haeundae Police Station. A logarithmic transformation was performed to ensure an effective statistical analysis and the number of theft crimes was used as the dependent variable. Related factors were selected through a literature review and divided into social, environmental, and defensive factors. Seven factors, were selected as independent variables: the numbers of foreigners, aged persons, single households, companies, entertainment venues, community security centers, and CCTV (Closed-Circuit Television) systems. OLS (Ordinary Least Squares) and GWR (Geographically Weighted Regression) were used to analyze the relationship between the dependent variable and independent variables. In the GWR results, each independent variable had regression coefficients that differed by location over the study area. The GWR model calculated local values for, and could explain the relationships between, variables more efficiently than the OLS model. Additionally, the adjusted R square value of the GWR model was 10% higher than that of the OLS model, and the GWR model produced a AICc (Corrected Akaike Information Criterion) value that was lower by 230, as well as lower Moran's I values. From these results, it was concluded that the GWR model was more robust in explaining the relationship between the number of thefts and the factors related to theft crime.

Keywords: Theft Crime, Spatial Pattern, Ordinary Least Squares, Geographically Weighted Regression

1. Introduction

In Korea, crime has been on the rise in recent decades. In 2015, 1,861,657 crimes were recorded, which represented an increase of about 4.6% compared with 2014. A review of the trend for 5 years (2011–2015) revealed that crime increased by 1.6%, on average, every year, except 2014, when it decreased by 4.2% (Korean Statistical Information Service, 2016). Recently, crimes against children, women and the elderly, and juvenile delinquency, have also increased. This increasing prevalence of crime is significantly impeding social development and restricting the quality of life of the general population. Much attention has been given to crime in studies from a diverse range of social sciences, including criminology (Park *et al*., 2014). Here, the most important aspect is to understand the context of crime, namely the 'where and when' of criminal events, to control and prevent their occurrence (Cahill and Mulligan, 2007).

Under these circumstances, research methods have mainly involved time series analyses using temporally or spatially aggregated data. However, such studies have limitations when considering the spatial distribution of incidents and crimes, and the primary characteristics of locations in which crimes occur (Walker *et al*., 2014). Because crime data essentially involves geographical attributes, an analysis of spatial patterns is very important in the analysis of

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crime (Park, 2000). In addition, crime data shows spatial dependency, being more similar in neighboring areas. This means that if the crime rate is high in a certain area, it is also likely to be high in neighboring areas. Similarly, if the crime rate is low, the crime rate of neighboring areas also tends to be low (Cheong and Hwang, 2010). In response to such characteristics, criminological researchers have recognized the importance of considering the non-stationarity of spatial processes and have paid more attention to local studies of crime (Cahill and Mulligan, 2007). In addition, the use of information technology and GIS (Geographic Information Systems) has enabled efficient analysis of spatial patterns of crime (Hwang and Hwang, 2003).

Recently, spatial regression models, such as the SEM (Spatial Error Model) and the SAR (Spatial Autoregressive) model, have been used to compensate for the shortcomings of the OLS (Ordinary Least Squares) method, and to capture the spatial non-stationarity of crime occurrences (Ceccato *et al*, 2002; Andressen, 2006; Jeong *et al*., 2009; Cheong and Hwang, 2010). Results published in the literature have shown that the explanatory power is increased when using SAR compared to OLS. However, in these studies, it was necessary to perform further spatial regression analysis because heteroscedasticity still existed.

GWR (Geographically Weighted Regression) is an excellent alternative method. GWR has been proposed as a technique to estimate the local parameters of spatial data, while considering spatial non-stationarity (Malczewski and Poetz, 2005; Cahill and Mulligan, 2007; Walker *et al*., 2014). Thus, it is necessary to determine how well the GWR model captures the spatial non-stationarity of crime occurrences and how much the GWR model improves accuracy compared with existing methods. Therefore, this study analyzed the spatial distribution of theft crimes at the level of census tracts using the GWR model and compared the results with those of the OLS model.

2. Study Area

The study area was Haeundae-gu, which is an established tourist area located in Busan. As of 2014, the total crime rate in Busan was highest in the district of Busanjin-gu (13.61%), followed by Nam-gu (10.99%), and Haeundae-gu (10.35%). The total crime rate in Haeundae-gu increased sharply in 1995 (by 7.90%), and the degree of increase was higher than in other regions (Korean Statistical Information Service, 2016). In addition, crime mapping in Busan using big data from 2014 indicated that Haeundae-gu was the most dangerous area of the city, and is the location where crime is most likely to happen in the future. The social polarization of the housing sector has become increasingly marked, and the chances of various types of crime occurring are high due

Fig. 1. Location and characteristics of the study area: (a) Administrative boundaries; (b) Census tract boundaries; (c) Crime rate trends in three major regions

to the number of summer vacationers and tourists (Busan, 2014). It was therefore considered that Haeundae-gu was a suitable region in which to analyze the spatial distribution of crime occurrence. In this study, a statistical analysis was conducted based on census tracts to determine the distribution of crimes at the regional scale. Haeundae-gu was divided into 705 census tracts (Fig. 1).

3. Data and Methods

3.1 Dependent and independent data

3.1.1 Dependent data: the number of crimes

Theft crime was selected for analysis in this study because it is the most frequently occurring of the five main categories of crime, i.e., homicide, robbery, sexual assault, violence, and theft. Data on the number of recorded thefts was acquired from the criminal records book held by Haeundae Police Station during the 5-year period from 2009–2013. The locations of the thefts were geocoded based on the addresses recorded in the book, and the number of thefts was calculated by summing the data for each census tract. The total number of thefts in the study area during the study period was 970. However, only the 795 thefts with identifiable addresses were used in the analysis. To perform an effective statistical analysis, the data were categorized by census tract and a logarithmic transformation was then performed. The log-transformed data were the dependent variable in both the OLS and GWR models.

3.1.2 Independent data: factors related to crime occurrence

The independent variables used in this study were selected based on a literature review. Based on data availability, social, environmental, and defensive factors were selected as independent variables (Table 1). The social factors used in this study were the numbers of foreigners, people aged 65 years and older, and single-person households. The numbers of foreigners and of people aged 65 years and older are known to influence the increase in crime rate (Kim *et al*., 2010; Jeong *et al*., 2009). Crimes involving elderly people are on the rise because of the aging society. Based on this phenomenon, we assumed that the numbers of people aged 65 years and older was correlated with the increasing crime rate. There is conflicting opinion on the impact of single-person households, on crime, although it has received much attention (Hwang and Hwang, 2003; Lee, 2004; Park *et al*., 2009). However, we expected that the probability of crime occurrence will increase depending on the effectiveness of human surveillance in areas where there are many single-person households.

The environmental factors were the numbers of companies and entertainment venues; these factors were selected

Table 1. Descriptive statistics for the independent variables used in this study

Class	Name	Description	Source
Crime		The number of theft occurrences	
Ln_crime		The log of theft occurrences	
Social			
Foreigners	For	The numbers of foreigners living in the area	NSO [a]
Aged persons	Old	The numbers of people aged 65 years and older	
Single household	Single	The numbers of single-person households	
Environmental			
Companies	Comp	The number of companies	NSO [a], PIP [b],
Entertain venues	Enter	The number of entertainment venues	HO [c]
Defensive			
Community security centers	Center	The number of community security centers	PIP, HO
Closed-circuit television	CCTV	The number of closed-circuit television systems	

[a] National Statistics Office; [b] Public Information Portal; [c] Haeundae-gu Office

because theft crimes usually occur in commercial areas. According to Lee and Cho (2006), there is a close correlation between entertainment venues and crime occurrence.

Representative defensive factors are the numbers of community security centers and CCTV (Closed-Circuit Television) systems. The main functions of community security centers are to improve crime surveillance and prevention. It was assumed that community security centers could play roles in decreasing crime occurrence. In addition, CCTV systems have an effect on decreasing crime occurrence because of their deterrent effect and the decreased fear of crime (Park *et al*., 2011; Lee *et al*., 2013).

Data on these factors were acquired from the NSO (National Statistics Office), the Haeundae-gu Office, and PIP (Public Information Portal). The environmental and defensive factors were geocoded based on the addresses at which the thefts were perpetrated and the number of thefts in each census tract was summed.

3.2 Spatial regression modelling

3.2.1 Ordinary least squares

Regression analysis is a global linear technique that is used to analyze and estimate relationships between a dependent variable and independent variables based on a linear equation. A simple regression analysis is used to analyze the relationship between one independent variable and the dependent variable, while a multiple regression analysis is used to analyze the relationship between more than one independent variable and the dependent variable. Because a stationary relationship was assumed across the study area, a single equation was used to represent the relationship between the dependent variable and the independent variables. This means that each independent variable has only a single coefficient and would thus have an equal impact throughout the whole study area. The equation used was Eq. (1).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \cdots\cdots \beta_n x_n + \varepsilon \tag{1}$$

where β_0 is the intercept, β_n is the parameter estimated for variable n, and x_n is a set of one or more independent variables (Mansour, 2015).

In the model, the parameters estimated for the variables were calculated using OLS. To accurately determine the parameter estimates, multicollinearity should be tested. When there is a strong correlation between more than two independent variables, this is often termed multicollinearity, and can be checked for using a multicollinearity diagnosis method, such as a test of TOL (Tolerance) or the VIF (Variance Inflation Factor). A TOL value < 0.1, and a VIF > 10, indicate significant multicollinearity between independent variables (Menard, 2002). Such variables should be excluded from an OLS model. ArcGIS ver. 10.2 (ESRI, Redlands, CA, USA) was used to apply the OLS model in this study.

3.2.2 Geographically weighted regression

The GWR model is a local regression model used to capture spatial non-stationarity in relationships between a dependent variable and independent variables. Instead of estimating only one parameter for each independent variable, the GWR model generates a set of local parameters for each data point within a study area (Cahill and Mulligan, 2007). Spatial non-stationarity is identified using local parameter estimates, local R-square values, local model residuals, and *t*-test values generated by the GWR model (Fotheringham *et al*., 2002). The GWR model can be expressed by Eq. (2).

$$y_j = \beta_0 \left(u_j, v_j\right) + \sum_{i=1}^{k} \beta_i \left(u_j, v_j\right) x_{ij} + \varepsilon_j \tag{2}$$

where u_j and v_j are the spatial position of location *j*, $\beta_0 \left(u_j, v_j\right)$ is the intercept, and $\beta_i \left(u_j, v_j\right)$ is the local estimated coefficient for independent variables (Su *et al*., 2012).

In a GWR model, parameters are estimated using a weighting function based on distance. It is assumed that locations that are closer to the estimation point have more influence on the estimation (Cahill and Mulligan, 2007). The distance decay functions can be calculated by Gaussian and bi-square techniques (Brunsdon *et al*., 1996; Fotheringham *et al*., 2002). In this study, the Gaussian distance decay was used to express the weight function that can be calculated using Eq. (3).

$$w_{ij} = \exp(-d_{ij}^2 \ / \ h^2) \tag{3}$$

where w_{ij} is the weight for observation j within the neighborhood of observation i, d_{ij} represents the distance between observations i and j, and h denotes the kernel bandwidth (Su *et al*., 2011).

The optimal kernel bandwidth can be selected using CV (Cross-Validation) and the AICc (Corrected Akaike Information Criterion). According to Fotheringham *et al*. (2002), the AICc is generally more applicable than the CV. Thus, in this study, the AICc was used to select the optimum bandwidth. The same dependent variable and independent variables included in the OLS model were also applied in the GWR model using ArcGIS software (ver. 10.2).

4. Results and Discussion

4.1 Ordinary least squares

The independent variables used in this study all had a VIF < 10. This indicates that there was no serious multicollinearity between the independent variables, most of which were statistically significant at the 1% level. The exceptions were aged persons (Old), single households (Single), and community security centers (Center), all of which were non-significant. This appears to reflect the characteristics of the theft incidents in this study, which usually occurred in business areas or community facilities rather than in residential areas. Community security centers were distributed homogeneously throughout the study area (Table 2).

All of the independent variables were positively associated with an increased number of thefts. Among the independent variables, CCTV had the largest influence on the number of thefts, with a correlation coefficient of 0.435. It was assumed that CCTV would serve to inhibit and deter crime. Based on this assumption, we expected the correlation between the number of CCTV systems and the number of crimes to be negative. However, the results revealed that as the number of CCTV systems increased, the number of thefts also increased. This might be because CCTV systems are usually installed in crime-prone areas and may also be installed by residents after a crime is committed, as a future deterrent.

In addition, the OLS model assumed normality and homoscedasticity of residuals. However, from the results, it was clear that there was spatial heterogeneity, because the Koenker statistic was significant at the 1% level. Because the Jarque–Bera statistic was also significant at the 1% level, the residuals were shown to be non-normally distributed. These results revealed that in the OLS model, the relationship between the dependent variable and the independent variables had spatial heterogeneity, and therefore the GWR model would be a more desirable choice.

4.2 Geographically weighted regression

Table 3 summarizes the estimated coefficients calculated for each independent variable. The average estimated coefficients for all independent variables were positive,

Table 2. Summary of the ordinary least squares results

Variable	Coefficient	Std. Error	t-Statistic	Probability	VIF
Intercept	-0.226	0.140	-1.617	0.106	-
For	0.036	0.013	2.783	0.006 *	1.220
Old	0.011	0.006	1.715	0.087	1.360
Single	0.001	0.001	0.435	0.664	1.466
Comp	0.025	0.001	22.251	1.3E-28 *	1.650
Enter	0.128	0.019	6.763	5.9E-10 *	1.505
Center	0.262	0.504	0.521	0.603	1.146
CCTV	0.435	0.136	3.188	0.002 *	1.104
Koenker (BP) statistic	0.000 *				
Jarque-Bera statistic	0.000 *				

* Statistically significant ($p < 0.01$)

per the results obtained with the OLS model. However, all independent variables showed both positive and negative associations with the number of crimes depending on the location within the study area. This result showed that the parameter estimates for independent variables had spatial heterogeneity in the study area (Fig. 2). For example, regarding the presence of CCTV, which had a significant effect on the number of thefts in the OLS model, 76% of the coefficients were positive and 24% were negative. Therefore, the GWR model estimated the influence of the independent variables more efficiently, by considering spatial heterogeneity through calculation of the local parameter estimates instead of using

Table 3. Descriptive statistics for the parameter estimates obtained from geographically weighted regression analysis

Variable	Mean	SD	Min	Max	% negative	% positive
Intercept	-0.177	0.501	-1.312	4.441	53.343	46.657
For	0.030	0.060	-0.826	0.116	23.898	76.102
Old	0.013	0.019	-0.016	0.103	25.462	74.538
Single	0.000	0.004	-0.026	0.012	57.468	42.532
Comp	0.020	0.007	-0.001	0.030	0.142	99.858
Enter	0.054	0.135	-1.178	0.291	15.647	84.353
Center	0.472	1.120	-2.631	9.640	17.496	82.504
CCTV	0.445	0.957	-0.609	4.474	23.898	76.102

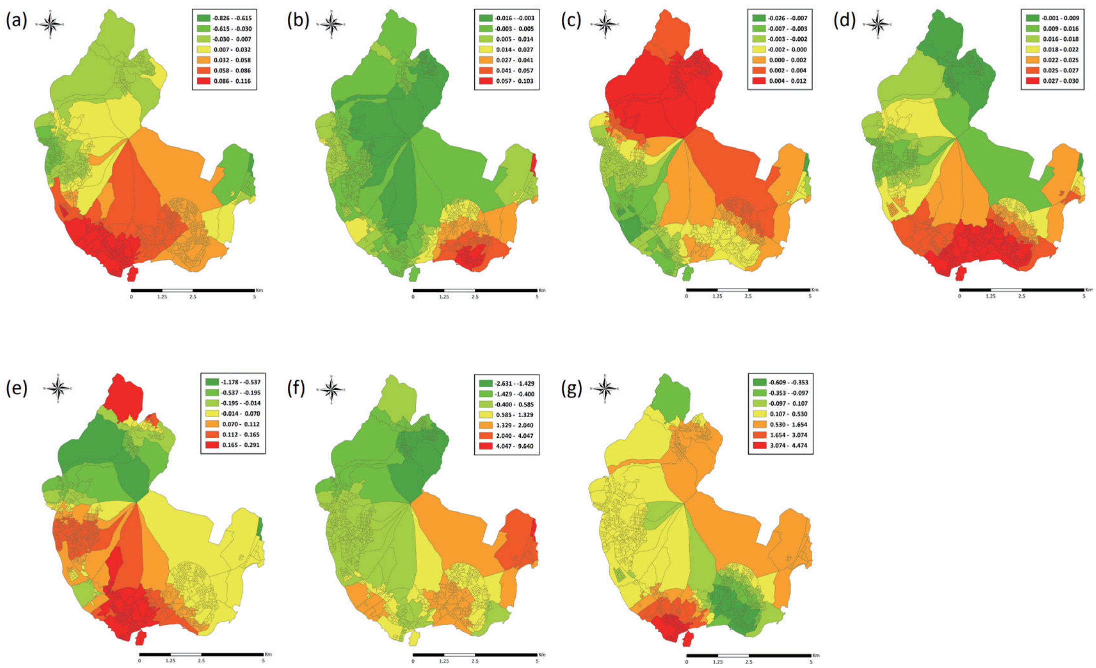

Fig. 2. Parameter estimation calculated by the GWR model for each independent variable: (a) Foreigners; (b) Aged persons; (c) Single households; (d) Companies; (e) Entertainment venues; (f) Community security centers; (g) CCTV systems

only one parameter estimate, as in the OLS model.

There were large differences in the R-square values by location; the values ranged from 0.04 to 0.87. Fig. 3 shows the spatial distribution of the R-square values calculated by the GWR model. The census tracts located in the lower part of the study area had higher R-squares, while the tracts in the upper part of the study area had lower R-square values. This result showed that there were variations in R-square values across the study area.

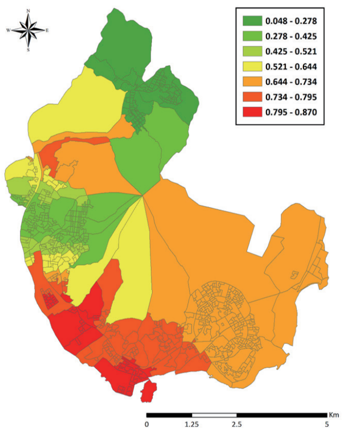

Fig. 3. Spatial distribution of the R-square values calculated by the GWR model

4.3 Comparison of the two regression models

The performance of the OLS and GWR models could be compared using the AICc and adjusted R-square values, and by spatial autocorrelation. Adjusted R-square values indicate how well a regression line is fitted, while the AICc is an information criterion used to measure the goodness-of-fit between models. Generally, a model with a high adjusted R-square value has greater explanatory power. In contrast, a model with a low AICc is considered superior, and when the difference between the two AICc values is more than 4, the models differ significantly (Carlton *et al*., 2009).

The adjusted R-square value of the OLS model was 0.651, while the corresponding value for the GWR model was 0.762. The explanatory power of the GWR model was 10% better than that of the OLS model. In addition, the AICc value of the GWR model was 2,390.285, which was much lower than that of the OLS model (2,919.431). This result showed that the GWR model was a better fit than the OLS model (Table 4).

Table 4. Comparison of the performance of the OLS and GWR models

Statistics index	OLS	GWR
Residual sum of squares		151.490
Corrected Akaike's information criterion (AICc)	2919.431	2690.285
Adjusted R-squared	0.651	0.762

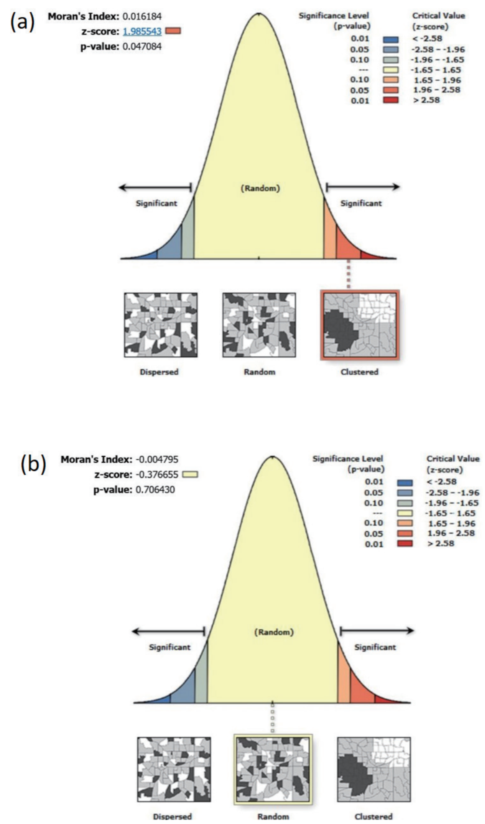

Fig. 4. Spatial autocorrelation of the standard residuals calculated by the OLS and GWR models. Moran's I for the (a) OLS and (b) GWR models

Fig. 4 shows the results of spatial autocorrelation of the standard residuals calculated by the OLS and GWR models. This analysis was conducted by calculating Moran's I values using ArcGIS software (ver. 10.2); the closer the value is to -1 or +1, the higher the degree of spatial autocorrelation; and the closer the value is to 0, the lower the degree of spatial autocorrelation. The Moran's I value of the OLS model was 0.016 and the z-score was 1.986. This result indicates that the OLS model could have a deficit in spatial autocorrelation. However, the results of the GWR model showed a better spatial autocorrelation, because the value of Moran's I (-0.004) and the degree of spatial autocorrelation were lower than those of the OLS model.

5. Conclusions

This study analyzed the relationship between the number of thefts and related factors, and determined the spatial patterns of theft crimes. In the OLS model, normality of distribution, homogeneity of variance, and independence of residuals were assumed. However, the results of an analysis using the Koenker statistic and Jarque–Bera statistic revealed violation of these assumptions, where the relationships between the dependent variable and the independent variables showed spatial non-stationarity and spatial autocorrelation. In the GWR model, each independent variable had parameter estimates that varied over the study area, rather than just one parameter estimate. The local R-square value ranged from 0.04 to 0.87 and displayed local variance. Compared to the OLS model, the adjusted R-square value in the GWR model was improved by 10%, and the value of AICc was lower by 230. Additionally, spatial autocorrelation was lower in the GWR model according to the Moran's I result.

According to these results, the GWR model is more efficient for analyzing the non-stationarity of theft crime. It is concluded that the influence of related factors on the theft crime differs by location. Therefore, policies that take account of local area characteristics should be applied to prevent and deter crimes across the study area. There were also some limitations to this study. First, there were differences in time scale between the dependent and independent variables used in this study. The dependent variable used the total crimes for 5 years, whereas the independent variables used the crimes for a given year. The main reason for this was the limits on data availability and low frequency of crime occurrence. In future studies, data should be collected in other administrative areas to avoid the difference in time scale and secure more comprehensive data. The effect of different-sized spatial units (e.g., administrative units) should also be considered. Second, only four of the included independent variables were significantly associated with the number of theft crimes. Additionally, the influence of these variables differed by location, even with respect to the directionality (negative or positive) of the parameter estimate. In future studies, more related factors should be included, which would improve the explanatory power of the models. Third, different types of crime might have different characteristics in terms of their spatial patterns. Thus, the spatial patterns of crimes such as homicide, robbery, sexual assault, and violence should be analyzed, and their characteristics compared.

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