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Spatial Regression Modeling Approach for Assessing the Spatial Variation of Air Pollutants

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Abstract: Over the past decades, industrialization has resulted in radical economic development in Korea. The resulting urban sprawl and unsustainable development have led to considerable air pollution. In this study, using spatial regression models, we examine the effects of the physical and socioeconomic characteristics of neighborhoods on particulate matter (PM_{10}, $PM_{2.5}$), NO_2, CO, and SO_2 concentrations in the Daegu Metropolitan area. Results reveal the following: (i) the socioeconomic characteristics were not statistically significant regardless of the air pollutant type; (ii) the effects of the built environment characteristics of the neighborhoods were different for each air pollutant. Compared with other pollutants, $PM_{2.5}$ was affected more by the built environment. Concerning the neighborhoods' main roads, the SO_2 concentration was higher, that of $PM_{2.5}$ was higher in neighborhoods with more bus stops, and those of CO and $PM_{2.5}$ were possibly higher in the neighborhood of industrial zones. In neighborhoods with parks and green areas, air pollutant concentrations are likely to be lower. When the total used surface of residential buildings was higher, the air pollutant concentrations were lower. Contextually, similar neighborhoods with more single-family houses seemed to have high pollution levels. Overall, this study is expected to guide policymakers and planners in making smart decisions for eco-friendly and healthy cities.

Keywords: air pollutants; built environment; spatial regression model; PM_{10}; $PM_{2.5}$; NO_2; CO; SO_2

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1. Introduction

Industrialization has led to major economic development in Korea over the past decades. Urban sprawl and indiscreet development have resulted in an increase in the use of automobiles and the construction of industrial facilities [1]. Air pollution is considered one of the most serious urban environmental problems worldwide [2]. Accordingly, various studies aimed at reducing air pollution have been conducted to achieve a sustainable urban environment [3–7]. Despite these efforts, air pollution is still a serious problem in many developed and developing countries worldwide for various reasons, including the use of fossil fuels and the increasing use of automobiles [8]. Moreover, air pollution poses a severe threat to people's health [9]. The World Health Organization (WHO) had reported that ~4.2 million people die annually from air pollution-related diseases. Moreover, ~91% of the world's population live in areas with air quality that does not meet the WHO's air quality standards [10]. Subsequently, many studies aiming at reducing air pollution have been conducted in Korea [11–15].

Prolonged exposure to high pollution levels due to particulate matter (PM) increases the risk of respiratory diseases and may even promote severe health problems such as diabetes [16,17]. In particular, $PM_{2.5}$ can cause heart disease. Moreover, it has been designated as a Group 1 carcinogen by WHO [18]. However, as of 2017, the average annual concentrations of PM_{10} and $PM_{2.5}$ in Korea were 45 and 25 $\mu g/m^3$, respectively, which exceeded the WHO standards of 20 and 10 $\mu g/m^3$. A 2016 Organization for Economic Cooperation and Development (OECD) report projected that among the OECD countries, premature deaths from air pollution in 2060 are expected to be the highest in Korea [19]. Therefore, Korea needs significant efforts to reduce overall air pollution and the PM_{10} and $PM_{2.5}$ concentrations. Although the severity of the $PM_{2.5}$ concentration in Korea is considerably high, it was not officially measured at the national level until 2015; as such, few studies on reducing $PM_{2.5}$ concentration exist. In addition, it is interesting that concentration of other pollutants, such as NO_2, CO, and SO_2, are not significant in Korea. The average annual concentrations of NO_2, CO, and SO_2 in Korea in 2017 were 0.022 ppm, 0.5 ppm, and 0.004 ppm, respectively, which were lower than the national ambient air quality standards. However, NO_2, CO, and SO_2 are considered major air pollutants and have been continuously managed for environmental sustainability. Therefore, in this study, we aimed to investigate the relationship between neighborhood characteristics and air pollutants by considering PM_{10} and $PM_{2.5}$, both of which are crucial for improving air quality in Korea, in addition to other pollutants, such as NO_2, CO, and SO_2. In particular, this study aims to identify the relationship between the socioeconomic characteristics of neighborhoods and various air pollutants.

Many studies have determined the correlation between air pollutants and the environmental characteristics of neighborhoods. In recent studies, among many such characteristics, land use characteristics, road and traffic characteristics, and land development characteristics have been frequently considered [20–25].

Chen et al. [26] classified heating and non-heating seasons and investigated the factors affecting NO_2 and PM_{10} concentrations in Tianjin, China; they reported that regardless of the air pollutant type, increased NO_2 and PM_{10} concentrations were observed in residential areas. This result is similar to those of the NO_2 study of Liu et al. [27] in Shanghai, China and the PM_{10} study of Wolf et al. [28]. However, Kim and Guldmann [29] analyzed the factors affecting the NO_2 levels as per the season in Seoul and demonstrated that the NO_2 concentration is low in residential areas in summer. Moreover, Weichenthal et al. [30] reported that the concentrations of $PM_{2.5}$ and ultrafine particles in Toronto, Canada, are generally low in residential areas. Furthermore, many studies have reported that unlike residential areas, regardless of the type of air pollutants, the concentrations of the pollutants are high in commercial areas [29,31,32]. Moreover, in many other studies, similar results were found for industrial areas [33–45].

In addition, parks and green areas have been considered land use factors affecting air pollution. It has been shown that the increase in green infrastructure lowers the concentrations of air pollutants [39,46–50]. Selmi et al. [49] analyzed the effect of air pollution by trees in Strasbourg, France, and found that the city-managed trees removed ~88 tons of pollutants in a year. However, they argued that although the trees in the city are an important factor in reducing air pollution, they are not the only solution. Therefore, it was recommended that urban environmental characteristics such as building structures and road design should be considered together. Cho and Choi [51] analyzed the factors affecting air pollutants in 17 regions in Korea and revealed that in the regions with higher percentages of green areas, the reduction in the PM_{10}, CO, and SO_2 concentrations, excluding NO_2 and O_3, is more effective. This result is similar to that of the study of Wolf et al. [28] in Augsburg, Germany. Moreover, Weichenthal et al. [30] investigated the effect of urban forms on air pollution in three Canadian cities: Montreal, Toronto, and Vancouver; their results revealed high concentrations of both $PM_{2.5}$ and ultrafine particles (UFP) in parklands, which was unexpected.

For road and traffic characteristics, the road width and proportion of roads in the area have been considered important factors in many studies, most of which have shown that regardless of the type of air pollutants, the air pollution concentration is higher when the road width or proportion of roads is higher [32,36,39,44]. Furthermore, Kim and Jun [12] analyzed the impact of urban characteristics on the air pollutant concentrations in the Seoul Metropolitan Region, Korea; they revealed that when the proportion of roads is higher, the concentrations of O_3, PM_{10}, and SO_2 are lower. Furthermore, traffic volume has been considered an important factor that significantly affects air pollutant concentrations [29,52–54].

Weichenthal et al. [31] examined the factors affecting air pollutants on a road segment in Toronto, Canada; they reported that the existence of more intersections leads to a higher $PM_{2.5}$ concentration. However, Kim and Jun [12] reported that in Korea, when the intersection rate is higher, the PM_{10} concentration is lower. Betancourt et al. [55] argued that having a dedicated bicycle lane on the sidewalk has a significant effect on reducing pollution exposure for cyclists compared with bicycles using mixed lanes. Furthermore, bus routes [13,31] and bus stops [35] have been considered road and traffic characteristics.

Land development characteristics have been considered in various studies [33,36,43]. Shi et al. [56] analyzed the association between the $PM_{2.5}$ concentration and building morphological design factors according to the season and revealed that regardless of the season, when the building height, building coverage proportion, and building volume density are higher, the $PM_{2.5}$ concentration is higher. This result is similar to that of Weichenthal et al. [32], which was conducted in Montreal, Canada. However, Habermann et al. [44] analyzed the factors affecting the NO_2 concentration in Gothenburg, Sweden, and reported that in areas where there are more skyscrapers, the NO_2 concentration was lower. Mavroidis and Griffiths [57] showed a similar result from an experimental simulation study on atmospheric pollution. He indicated that the presence of taller building facilitates the vertical detrainment of pollutants, thereby decreasing their ground-level concentrations. Moreover, Oh and Chung [58] investigated the effect of NO_2 and PM_{10} concentrations on the urban development density in Seoul, Korea, and reported that when the gross residential floor area is high, the NO_2 and PM_{10} concentrations are high. However, the high gross commercial and business floor areas seemed to increase only the NO_2 concentration and not the PM_{10} concentration. Furthermore, Farrell et al. [45] argued that a greater number of commercial facilities is likely to increase the $PM_{2.5}$ concentration.

Hence, the association between air pollutants and the built environment has been investigated in many countries. Nevertheless, environmental damage such as air pollution may be concentrated mainly in areas that are socioeconomically disadvantaged [59,60]. The socioeconomically disadvantaged population is more likely to live in areas with relatively vulnerable environments. This environmental inequality, in addition to the social inequalities of income, health, employment, education, and housing, has become the primary factor of social inequality among income classes and is expected to worsen over time [61]. Therefore, research on air pollution needs to consider both the physical environment characteristics and the socioeconomic aspects of a neighborhood. In fact, Pearce et al. [62] studied the distribution of air pollution from the perspective of environmental justice in Christchurch, New Zealand. The results showed that various social groups in the Christchurch area were exposed to extreme air pollution. In particular, it was found that pollution was quite high in communities where the vulnerable lived. However, very few studies have investigated the link between air pollution and socioeconomic characteristics of neighborhoods, as well as the built environment of neighborhoods. Therefore, this study aimed to investigate the correlation between air pollutants and the overall neighborhood environment characteristics while considering both the built environment and socioeconomic factors.

2. Materials and Methods

2.1. Study Area

The present research was conducted in the Daegu Metropolitan City, which is an industrial metropolis in Korea. In this study, the administrative district (Dong), which is generally recognized as a neighborhood in Korea, was defined as a spatial unit. In this study, we investigated the PM_{10}, $PM_{2.5}$, NO_2, CO, and SO_2 concentrations for an average of three years (from 2016 to 2018). The air pollution data were provided by the Air Korea, Korea Environment Corporation, which is a government organization under the Ministry of Environment in Korea.

As of 2018, the Daegu Metropolitan City had a population of ~2.46 million and an area of ~884.15 km^2. The total area was divided into residential area (49.3%), commercial area

(12.3%), industrial area (3.9%), and other green and management areas (34.5%). Based on the annual average of the PM_{10} concentrations by region, Daegu City ranked second among the cities with the highest concentration in Korea [63]. In 2017, mean $PM_{2.5}$ concentrations in Daegu City reached 24 μg/m^3, which was more than double the WHO standard [63]. Moreover, it had higher air pollution concentrations of SO_2, NO_2, and CO in comparison with other cities in Korea [63]. As of 2017, the number of vehicles registered in Daegu Metropolitan City was approximately 1.16 million, with the city ranking the 4th highest among seven metropolitan cities in Korea. In particular, the ratio of passenger cars to all vehicles in Daegu Metropolitan City accounts for 82.7%, which is slightly lower than the average passenger car ratio of 83.1% in seven metropolitan cities in Korea. However, the percentage of heavy vehicles (17.1%) in Daegu Metropolitan City was higher than the average of 16.6% in seven metropolitan cities [63]. The data clearly shows that Daegu Metropolitan City has more heavy vehicles than other metropolitan cities in Korea.

2.2. Air-Monitoring Stations

Information on air monitoring stations and air pollutant concentrations was obtained from Air Korea, which provides the data on the outdoor air quality nationwide under the Korean Ministry of Environment [64]. There are 11 types of air-monitoring stations, with a total of 533 stations located in 111 cities nationwide. Daegu Metropolitan City has 15 air-monitoring stations in operation, including 13 urban and two roadside air–monitoring stations. The height of urban air-monitoring stations is deliberately set in the range of 1.5 m to 10 m above the ground, where people normally live. Similarly, roadside air-monitoring stations are usually set between 1.0 m to 10 m above the ground. Additionally, they are installed in places where buildings or topographical obstacles would not interfere, in order to accurately record the level of pollution in the area. Urban and roadside air-monitoring stations take measurements at 1-hr intervals, and concentrations of SO_2, CO, NO_2, PM_{10}, $PM_{2.5}$, and O_3, as well as wind direction, wind speed, temperature, and humidity are measured. Figure 1 shows the locations of the 15 air-monitoring stations distributed across Daegu.

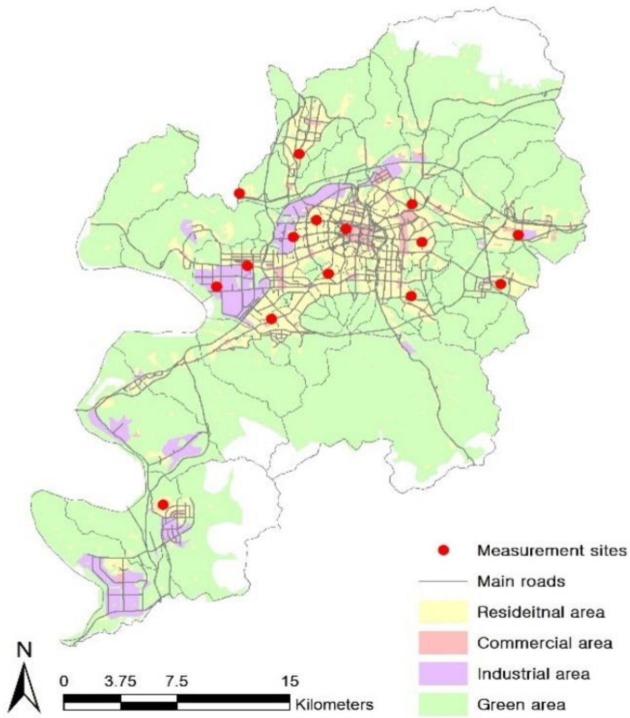

Figure 1. Air-monitoring stations in Daegu.

2.3. Data Analysis

In this study, we considered the road traffic characteristics, land-use characteristics, land development characteristics, and socioeconomic characteristics of the neighborhoods that can be associated with air pollutants. Table 1 gives the definition of variables. The socioeconomic factors include the proportions of the population below the age of 15 and over the age of 65 and the proportion of the national basic livelihood security recipients. Data of socioeconomic factors were obtained by contacting Korean Statistical Information Service (KOSIS) [65] and Daegu City directly.

Table 1. Variable descriptions.

Classification	Variables	Descriptions
Dependent variables	PM_{10}	2016–2018 average PM_{10} concentration in Daegu
	$PM_{2.5}$	2016–2018 average $PM_{2.5}$ concentration in Daegu
	NO_2	2016–2018 average NO_2 concentration in Daegu
	CO	2016–2018 average CO concentration in Daegu
	SO_2	2016–2018 average SO_2 concentration in Daegu
Socioeconomic characteristics	Children under 15 years	Ratio of people under 15 years to the total population
	Elderly above 65 years	Ratio of people above 65 years to the total population
	National basic livelihood security recipient	Ratio of national basic livelihood security recipients to the total population
Road characteristics	Neighborhoodstreet	Ratio of neighborhood streets to the total road
	Main road	Ratio of main roads to the total road
	Intersection	Number of intersections per unit area
	Bus stop	Number of bus stops per unit area
Land-use characteristics	Residential area	Ratio of residential areas to the total area
	Commercial area	Ratio of commercial areas to the total area
	Industrial area	Presence of industrial areas (1 = presence, 0 = otherwise)
	Park and green area	Ratio of park and green areas to the total area
	Mixed land use	Degree of mixed land uses (0(single use) to 1(mixed use))
Land development characteristics	Total used surface of residential buildings	Sum of total used surfaces of residential buildings
	Total used surface of commercial buildings	Sum of total used surfaces of commercial buildings
	Single-family housing	Number of single-family houses per unit area
	Multifamily housing	Number of multifamily houses per unit area

Road and traffic characteristics include intersection density, bus stop density, and the proportion of streets and main roads in the neighborhoods, which were considered to understand the difference in the effect according to road width. These road and traffic data were obtained from the National Spatial Data Infrastructure (NSDI) portal [66], Road Name Address Developer Center [67], and Korean Transport Database (KTDB) [68].

For the land-use characteristics, the proportion of the residential areas, commercial areas, parks, and green areas and the presence of industrial areas were considered. Land use data were obtained from the NSDI portal [66] and Road Name Address Developer Center [67]. Finally, for the land development characteristics, the total used surface of residential and commercial buildings, density of single-family houses, and density of multifamily houses were considered. These land development data were obtained from the NSDI portal [66] and analyzed.

2.4. Methods

2.4.1. Spatial Measures

In this study, an interpolation was performed to measure the air pollution concentration at the neighborhood level [11]. This analysis method is appropriate for reasonably calculating the values of unmeasured points [69]. All air-monitoring stations in Daegu were geocoded with the help of the geocoding tool of GIS (Geographic Information System).

Additionally, the three–year (2016–2018) average concentrations of PM_{10}, $PM_{2.5}$, NO_2, CO, and SO_2 measured at each air-monitoring station were geocoded. The interpolation was conducted by GIS to measure the distribution of air pollutants at the neighborhood level using zonal statistics.

2.4.2. Spatial Regression Model

Air pollutants generally exhibit spatial attributes when moving in air. Therefore, because the spatial correlation between nearby regions is highly probable, a spatial regression model that can control the spatial autocorrelation should be used. If an ordinary least-squares (OLS) regression model is used instead of the spatial regression model, the spatial autocorrelation cannot be controlled and the results of the analysis can be biased [70]. In this study, we employed the spatial regression model to control the spatial autocorrelation using GeoDa program. GeoDa is a free and open-source software program for the spatial data analysis developed by Dr. Luc Anselin and his team [71]. GeoDa can facilitate the new understanding of spatial econometric models by conducting the spatial lag model (SLM) and spatial error model (SEM) [72].

SLM is a method for controlling the spatial autocorrelation of a dependent variable when the dependent variable has a spatially dependent relationship. A statistically significant value of ρ indicates that the spatial autocorrelation of the dependent variable needs to be considered. This is because the focus of attention is an assessment of the existence and intensity of spatial interactions. The SLM equation is then expressed as follows:

$$y = \rho Wy + X\beta + \varepsilon \tag{1}$$

where ρ denotes a spatial autoregressive coefficient, W is a spatial weight matrix ($N \times N$ spatial lag operator), Wy is a spatially lagged dependent variable, X is an explanatory variable, β is a K by 1 vector of parameters, and ε is a vector of error terms. Unlike SLM, SEM is a method that controls the error portion of the error term when the error terms are dependent on each other. For SEM, when a lambda value is statistically significant, it indicates that the spatial autocorrelation of the error term is controlled. The SEM equation is then expressed as follows:

$$y = X\beta + \varepsilon \tag{2}$$

$$\varepsilon = \lambda W\varepsilon + u \tag{3}$$

where X is an explanatory variable, β is a K by 1 vector of parameters, ε is a spatially dependent error term, λ is a spatial autoregressive parameter, W denotes a spatial weight matrix, and u is a spatially uncorrelated error term. In this study, y denotes the average air pollution concentration in the neighborhood for three years according to the type of air pollutants, X denotes the socioeconomic and built environment characteristics of the neighborhoods, and W denotes the spatial correlation among the neighborhoods.

3. Results and Discussion

3.1. Spatial Distribution of Air Pollutants

Figures 2–6 show the spatial distributions of the air pollutants measured in a neighborhood in the Daegu Metropolitan City through spatial interpolation.

In general, the air pollution in Daegu was low in the eastern and southern regions and high in the western and northern regions. The spatial distribution of the air pollutants demonstrates a difference in the spatial distribution by the type of air pollutants. The PM_{10} concentration is likely to be high in the northwestern part of Daegu, given that since 1970, major industrial facilities have been located in the northwestern region of Daegu, such as the Seodaegu Industrial Complex that is mainly occupied by textile companies and the Dyeing Industrial Complex. These industrial areas are located very close to the downtown area of Daegu City, where other air pollution concentrations are high.

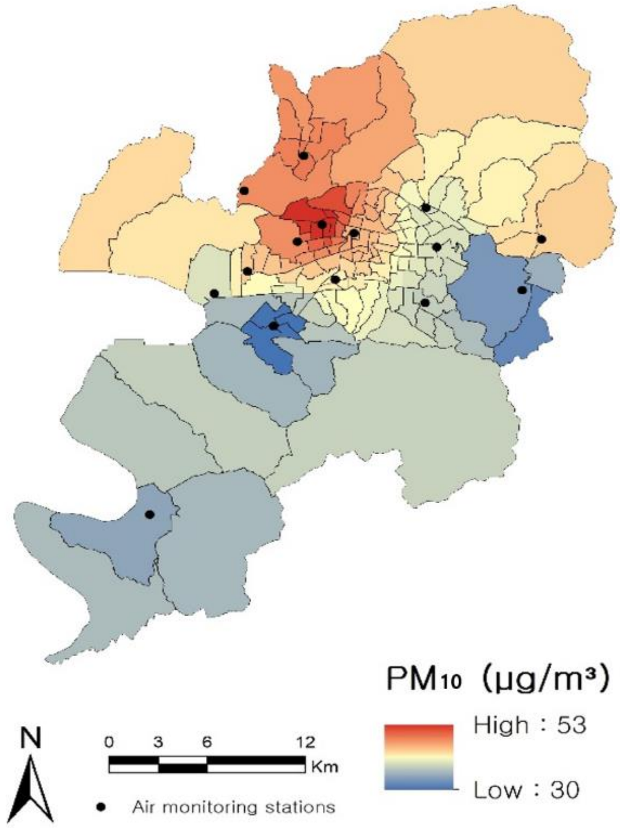

Figure 2. Spatial distribution of particulate matter PM_{10}.

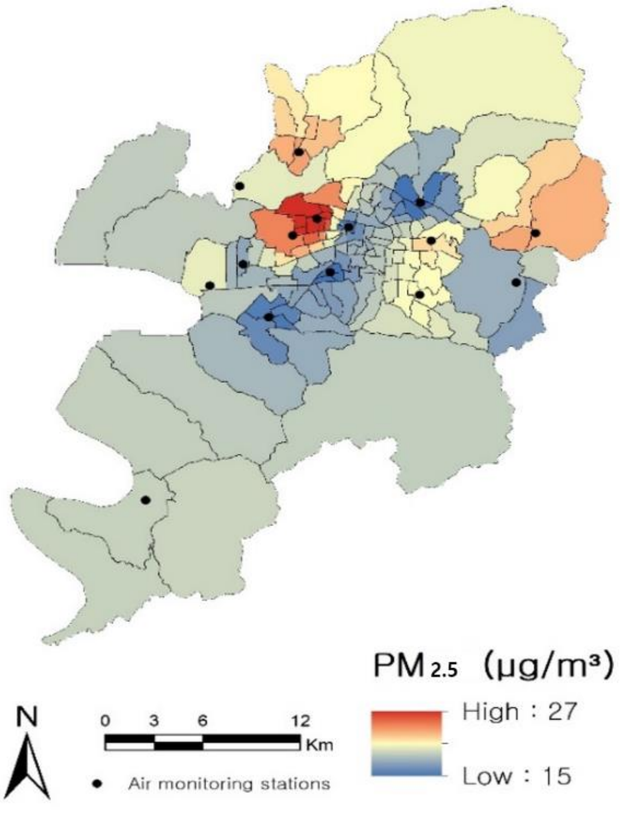

Figure 3. Spatial distribution of $PM_{2.5}$.

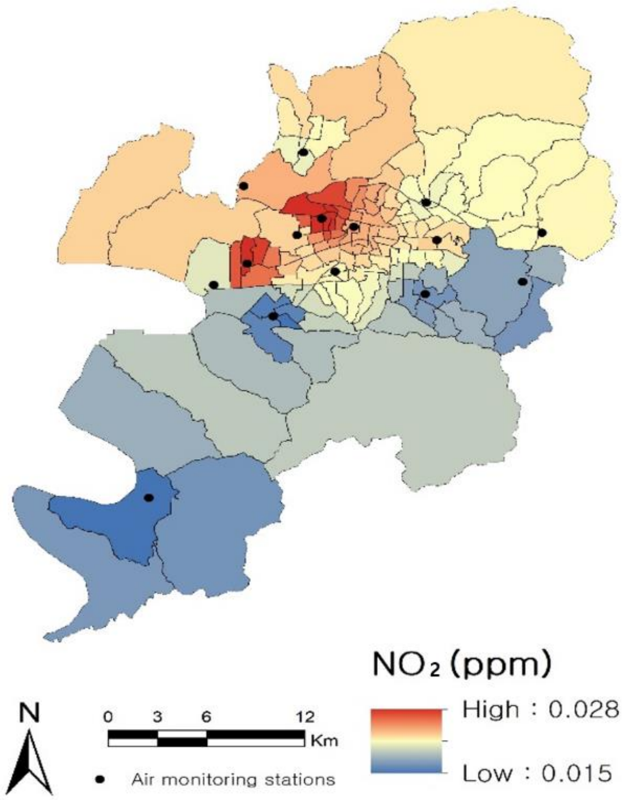

Figure 4. Spatial distribution of NO_2.

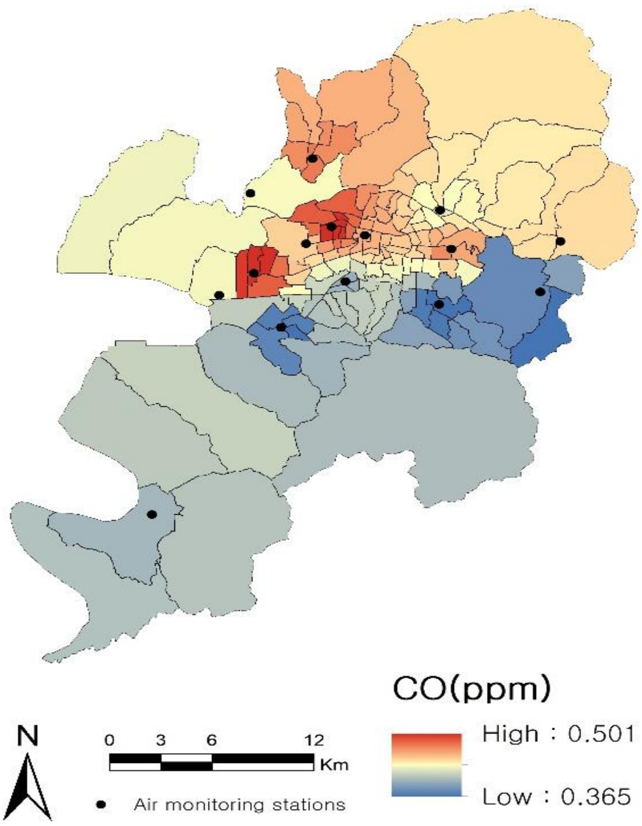

Figure 5. Spatial distribution of CO.

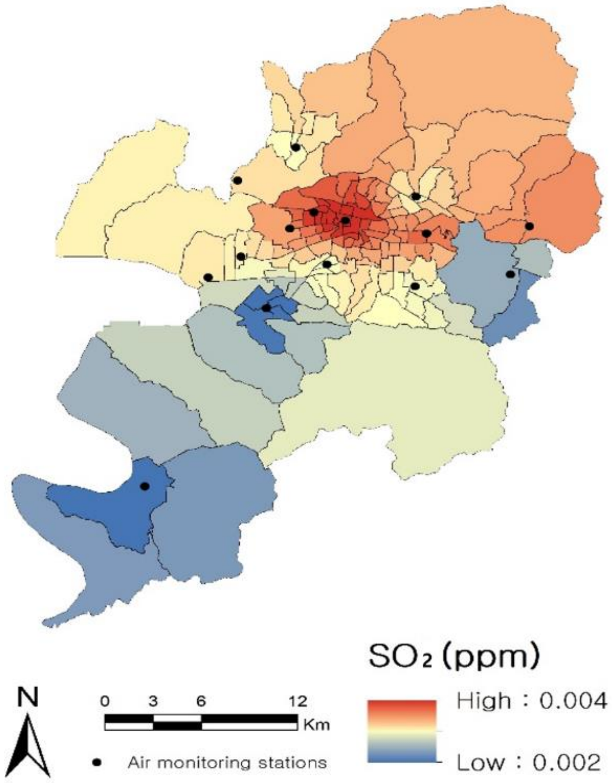

Figure 6. Spatial distribution of SO_2.

The spatial distribution of $PM_{2.5}$ was less than that of PM_{10}, but the $PM_{2.5}$ concentration was relatively low in the downtown area of Daegu, unlike PM_{10}. In particular, unlike other pollutants, the spatial distribution of $PM_{2.5}$ tended to be extremely high in specific areas. This finding indicates that $PM_{2.5}$ is a very light pollutant compared with other pollutants and that the $PM_{2.5}$ concentration is primarily high in the area where the source of $PM_{2.5}$ exists. Therefore, $PM_{2.5}$ does not seem to spread to other areas and seems to be easily diluted in the atmosphere.

The spatial distributions of NO_2 and CO generally exhibit a similar spatial pattern. Similar to PM_{10} and $PM_{2.5}$, the concentrations of NO_2 and CO are likely to be high in the northwestern regions. However, the NO_2 and CO concentrations were extremely high in the western regions of Daegu, where the concentrations of PM_{10}, $PM_{2.5}$, and SO_2 were relatively low. In the western region of Daegu City, the Daegu Seongseo Industrial Complex was established as a scientific industrial complex between 1990 and early 2010. These results indicate that pollution emissions even in the same industrial areas are different depending on the type of industrial facilities. In particular, unlike other pollutants, the concentration of SO_2 is likely higher in the downtown area of Daegu. In conclusion, in the case of Daegu, the factories are concentrated in a specific area and the traffic of vehicles is also relatively concentrated in the downtown area; thus, air pollutants interacting with specific factors are not continuous but appear high in specific areas.

3.2. Verification of the Spatial Autocorrelation

Table 2 presents the results of the spatial autocorrelation analysis of air pollutants using Moran's I test. Moran's I test is used to evaluate whether the spatial pattern distributed is clustered, dispersed, or random [71]. Moran's I value ranges from −1 to +1. A value close to +1 indicates clustering of similar values, while a value close to −1 indicates clustering of dissimilar values. These results confirm that all the air pollutants considered in this study have a spatial autocorrelation. Therefore, a spatial regression model that can control the spatial autocorrelation should be used. In this study, the effects of the neighborhood environment characteristics on the PM_{10}, $PM_{2.5}$, NO_2, CO, and SO_2 concentrations in Daegu were investigated using spatial regression models that can control the spatial autocorrelation rather than an ordinary least-squares regression model.

Table 2. Results of the spatial autocorrelation analysis.

Dependent Variable	Moran's I	Z-Score
PM_{10}	0.435	31.752
$PM_{2.5}$	0.287	21.148
NO_2	0.394	28.835
CO	0.338	24.753
SO_2	0.459	33.417

3.3. Descriptive Statistical Analysis

The descriptive statistics of the neighborhood environment variables are given in Table 3.

Table 3. Descriptive statistics.

Classification	Variables	Units	Mean	Std. Dev
Dependent variables	PM_{10}	$\mu g/m^3$	41.370	3.930
	$PM_{2.5}$	$\mu g/m^3$	19.720	2.180
	NO_2	ppm	0.020	0.002
	CO	ppm	0.427	0.028
	SO_2	ppm	0.003	0.000
Socioeconomic characteristics	Children under 15 years	%	10.651	4.000
	Elderly above 65 years	%	16.180	4.947
	National basic livelihood security recipient	%	5.375	4.425
Road characteristics	Neighborhood street	%	41.887	24.260
	Main road	%	49.093	25.308
	Intersection	$Number/km^2$	121.30	135.32
	Bus stop	$Number/km^2$	11.242	6.850
Land use characteristics	Residential area	%	49.330	29.426
	Commercial area	%	12.325	16.818
	Industrial area	0 or 1	0.19	0.397
	Park and green area	%	5.364	9.337
	Mixed land use	0–1	0.322	0.157
Land development characteristics	Total used surface of residential buildings	m^2	524,222	378,931
	Total used surface of commercial buildings	m^2	195,895	151,254
	Single-family housing	$Number/km^2$	955.83	914.23
	Multifamily housing	$Number/km^2$	86.337	106.17

The average concentrations of dependent variables are calculated based on the average of all administrative districts in Daegu. The average concentrations of PM_{10} and $PM_{2.5}$ in Daegu were ~41.37 and 19.72 $\mu g/m^3$, respectively. These concentration levels were more than double WHO's recommended PM_{10} and $PM_{2.5}$ annual averages of 20 and 10 $\mu g/m^3$, respectively, which indicates that Daegu's particulate matter contamination was very serious from 2016 to 2018. Furthermore, the average concentrations of NO_2, CO, and SO_2 were 0.02, 0.427, and 0.003 ppm, respectively. The NO_2 concentration is close to the WHO standard of 0.021 ppm, while the SO_2 concentration is lower than the WHO standard of 0.019 ppm.

For the socioeconomic characteristics of neighborhoods, the proportion of the population below 15 years was ~10.65% and that over 65 years was ~16.18%. In Daegu City, the population of elderly people over 65 years was higher than that of young people below 15 years. Furthermore, the proportion of the national basic livelihood security recipients was ~5.4% of the total population.

For the road characteristics, the neighborhood streets, which were primarily designed for pedestrian traffic, accounted for ~42%. However, the proportion of the main roads, which were designed for vehicle traffic, accounted for ~49%. The average density of the intersections in the neighborhood was ~135 intersections per km^2, and the average density of the bus stops in the neighborhood was about seven bus stops per km^2.

For the land-use characteristics, on average ~49% of the neighborhoods were residential, whereas commercial areas were less common (~12%). Furthermore, ~20% of all the neighborhoods in Daegu had industrial areas. The neighborhoods in Daegu had ~5.4% parks and green areas, and the mixed land use had a value between 0 and 1. A value closer to 0 indicates single use, whereas a value closer to 1 indicates mixed land use [72]. The average mixed land use of the neighborhoods in Daegu was ~0.322.

For the land development characteristics, the average sum of the total used surface of residential buildings in the neighborhood was ~524,222 m^2, and the average sum of the total used surface of commercial buildings was ~195,895 m^2. On average, there were ~914 single-family houses and ~106 multifamily houses per km^2 in the neighborhood.

3.4. Results of the Spatial Regression Models

The results of the spatial regression model analysis of the association between the concentrations of the air pollutants and the neighborhood environment characteristics according to the air pollutant types are given in Appendix A Tables A1 and A2. Some differences were observed between the OLS model, which does not control the spatial autocorrelation, and the SLM and SEM models, which control the spatial autocorrelation. In this study, the spatial regression models were more suitable than the OLS model because the statistical significance of both the SLM and SEM models was obtained from the Lagrange multiplier (LM) test for selecting the optimal model. Unlike some previous studies [36,39] that did not consider the spatial autocorrelation, these results indicate that the spatial regression model that can control the spatial autocorrelation should be used to consider the spatial properties of air pollutants. However, the robust LM results indicate a statistical significance in the robust LM lag for all the air pollutants, but such a significance was not observed in the robust LM error. Furthermore, the log-likelihood, Akaike information criterion (AIC), and Schwarz criterion (SC) values, which present the suitability of the models, indicate that regardless of the type of air pollutants, the SLM model is the most suitable. Therefore, in this study we adopted the SLM model as the final model. Table 4 gives a summary of the SLM results of analyzing the association between the neighborhood environment characteristics and the air pollution concentrations by the type of air pollutants.

No statistical significance was observed in the variables considered for examining the effects of socioeconomic characteristics of the neighborhoods on air pollution. Spatial statistical significance in the data is achieved when the z-score of variables falls outside the range between −1.96 and +1.96 at the 95% confidence level, or between −2.58 and +2.58 at the 99% confidence level [73]. However, Choi et al. [74] investigated 133 municipalities in Korea and demonstrated that national basic livelihood security recipients had a negative association with air quality. When inhaled, $PM_{2.5}$ can cause serious health problems, such as respiratory and cardiovascular diseases; moreover, it has a particularly serious effect on both children and the elderly [75,76]. Therefore, in addition to cross-sectional research, such as that in this study, a time-series study using panel data is required to have a better understanding of the association between the socioeconomic characteristics of the neighborhoods and the air pollutants.

Table 4. Summary of the spatial lag models of the air pollutants.

Classification		PM_{10}		$PM_{2.5}$		NO_2		CO		SO_2	
		Coefficient	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**	**Coefficient**	**Z**
Socioeconomic characteristics	Children under 15	0.008	0.257	0.007	0.300	0.000	0.093	0.000	0.520	0.000	1.640
	Elderly above 65	0.005	0.165	0.008	0.348	−0.000	−0.406	−0.000	−0.206	0.000	1.315
	National basic livelihood security recipient	0.011	0.431	0.005	0.253	−0.000	−0.264	0.000	0.029	0.000	1.310
Road characteristics	Neighborhood road	0.002	0.230	0.006	0.989	0.000	0.766	0.000	1.705	0.000	1.645
	Main road	0.004	0.530	0.005	0.818	0.000	0.551	0.000	1.509	0.000 *	2.214
	Intersection	−0.099	−0.725	−0.197	−1.902	−0.000	−1.057	−0.001	−1.314	−0.000	−0.949
	Bus stop	0.073	0.404	0.278 *	2.0247	−0.000	−0.225	0.002	0.167	0.000	1.865
Land-use characteristics	Housing area	−0.013 *	−2.017	−0.004	−0.881	−0.000	−1.422	−0.000	−0.857	−0.000 *	−2.220
	Commercial area	−0.017	−1.941	−0.015 *	−2.323	−0.000	−0.864	−0.000	0.343	−0.000	−1.568
	Industrial area	0.504	1.661	0.453 *	1.984	0.000	1.666	0.006 *	2.196	0.000	1.739
	Park area	−0.160	−1.810	−0.132 *	−2.001	−0.000	−1.034	−0.001	−1.289	−0.000	−1.933
	Mixed use	0.503	0.617	−0.220	−0.359	0.000	0.449	0.007	0.920	0.000	0.452
Development density characteristics	Total used surface of residential buildings	−0.000 *	−2.229	−0.000	−1.176	−0.000 *	−2.199	−0.000 *	−2.067	−0.000	−1.906
	Total used surface of commercial buildings	0.000	0.419	0.000	0.563	−0.000	−0.000	0.000	0.016	0.000	1.615
	Single-family housing	0.381 **	2.963	0.138	1.430	0.000 **	2.950	0.002	1.920	0.000 **	3.287
	Multifamily housing	0.034	0.251	0.066	0.646	0.000	0.203	0.000	0.501	−0.000	−0.268
Rho		0.959 **	49.953	0.966 **	54.931	0.936 **	36.302	0.932 **	35.142	0.915 **	32.374
Lagrange multiplier (LM) lag		186.04 **		172.21 **		152.90 **		160.48 **		123.41 **	
LM error		120.86 **		123.84 **		103.49 **		111.16 **		60.612 **	
Robust LM lag		65.344 **		50.356 **		49.563 **		49.575 **		62.952 **	
Robust LM error		0.160		1.985		0.148		0.256		0.154	
Log likelihood		−214.80		−175.92		785.33		426.75		1061.94	
N		139		139		139		139		139	
R^2		0.938		0.886		0.888		0.880		0.925	
Akaike information criterion (AIC)		465.60		387.85		−1534.66		−817.51		−2087.88	
Schwarz criterion (SC)		518.42		440.67		−1481.84		−764.69		−2035.06	

* $p < 0.05$, ** $p < 0.01$.

For the road and traffic characteristics, the main roads did not have a statistical significance with the air pollutants, except for SO_2 (coefficient = 0.000, p = 0.02). In areas with more main roads, the SO_2 concentration was higher. However, studies have previously reported contradictory results. Major roads are likely to increase the $PM_{2.5}$ [35,39], NO_2 [37,77], CO [78], and PM_{10} [26] concentrations, and the neighborhood streets are not associated with all the air pollutants. However, Muttoo et al. [24] and Cordioli et al. [33] indicated that when minor and major roads are longer, the NO_2 concentration is higher. Weichenthal et al. [30] demonstrated that local roads as well as highways are likely to increase the $PM_{2.5}$ concentration. Han and Naeher [79] indicated that CO is one of the major traffic-related air pollutants because of incomplete combustion of fuels in traffic engines. They also showed CO concentration in urban areas is highly influenced by traffic congestion and traffic density. The results of this study, which are contrary to those of the previous studies, suggest that it is necessary to consider the hierarchy of the roads and influencing variables such as traffic volume.

There is no statistically significant correlation between density of intersections and any of the pollutants. However, Hankey and Marshall [35] investigated the on-road particular air pollution using mobile monitoring in Minneapolis, USA, and reported that when the number of intersections is higher, the $PM_{2.5}$ concentration is lower. Therefore, special attention should be drawn to the effect of the negative direction of the intersections on all the air pollutants in this study.

The bus stops were only associated with $PM_{2.5}$ (coefficient = 0.278, p = 0.04). In areas with more bus stops, the $PM_{2.5}$ concentration was higher. This result is consistent with the study of Hankey et al. [35], which confirms that when the number of bus stops is higher and the bus routes are longer, the pollution level of $PM_{2.5}$ is higher. Therefore, exhaust gas reduction systems such as diesel particulate filters (DPFs) should be mandatory for heavy-duty diesel buses so as to reduce the $PM_{2.5}$ emissions [80]. Furthermore, the development of various policies and programs is required, such as sustainable management and restrictions on old buses that emit more air pollution owing to lack of particulate filters and incomplete combustion. In addition, human behavioral factors such as smoking while waiting for a bus were reported to increase the $PM_{2.5}$ concentration around bus stops [81]. Since 2011, Korea has designated all bus stops as no-smoking areas. However, the management of or penalties on this regulation are still insufficient. To reduce the concentration of $PM_{2.5}$ in terms of public health, smoke supervision around bus stops should be strengthened. Furthermore, Sahu et al. [82] conducted a study on the emission inventory of anthropogenic $PM_{2.5}$ and PM_{10} in Delhi, India, and revealed that $PM_{2.5}$, unlike PM_{10}, accounts for 45% of the emissions by vehicles such as buses in comparison with other factors.

Among the five land-use characteristics, only industrial areas exhibited a positive correlation with any of the pollutants, regardless of statistical significance. The positive association of the industrial areas with all the air pollutants (PM_{10}: coefficient = 0.504, p = 0.09; $PM_{2.5}$: coefficient = 0.453, p = 0.04; NO_2: coefficient = 0.000, p = 0.09; CO: coefficient = 0.006, p = 0.02; SO_2: coefficient = 0.000, p = 0.08) indicates that special environmental management of the industrial areas is necessary. Moreover, the mixed land use had no effect on all air pollutants. The residential areas were found to be associated with PM_{10} (coefficient = -0.013, p = 0.04) and SO_2 (coefficient = -0.000, p = 0.02); this result may reveal the distinctive characteristics of residential areas in Korea. Generally, most of the residential areas in Korea are highly and densely developed neighborhoods that primarily comprise multifamily houses. In Korea, high-density, multifamily residential development projects should construct green parks in their residential complexes according to the development regulations. Green areas and parks in multifamily housing complexes can play a significant role in reducing the concentrations of air pollutants [83]. This result agrees with the negative direction between air pollutants and green areas. In particular, parks and green areas have proven effective in reducing $PM_{2.5}$ (coefficient = -0.132, p = 0.04) concentrations. Moreover, when the total used surface of residential buildings was higher, the concentrations of all the air pollutants were lower. In particular, CO (coefficient = -0.000,

p = 0.03), NO_2 (coefficient = −0.000, p = 0.02), and PM_{10} (coefficient = −0.000, p = 0.02) had a negative association with the total used surface of residential buildings. Therefore, promoting eco-friendly development is necessary for high-density, multifamily residential projects, which can be realized by providing more parks and green spaces.

This study demonstrates that commercial areas were negatively associated with only $PM_{2.5}$ (coefficient = −0.015, p = 0.02). The concentration of $PM_{2.5}$ was lower when there were more commercial areas in a neighborhood. Figure 3 shows a possible explanation for this finding of the spatial distribution of $PM_{2.5}$. The concentration of $PM_{2.5}$ was relatively low in the downtown area located at the center of the Daegu Metropolis. Commercial areas tend to have a higher pedestrian flow than other land-use areas. $PM_{2.5}$ is composed of very small particulate matter, unlike other air pollutants in gaseous form. Therefore, the static electricity generated on the clothes of many pedestrians in commercial areas can attract $PM_{2.5}$ [84–86]. Therefore, to minimize the exposure to $PM_{2.5}$, which is designated as a class 1 carcinogen and has adverse effects on the human body, various policies and programs must be considered at the micro level, including projects that are related to architecture, urban design, and macro-level approaches.

The industrial areas were reported to be associated with CO (coefficient = 0.006, p = 0.02) and $PM_{2.5}$ (coefficient = 0.453, p = 0.04), and the concentrations of $PM_{2.5}$ and CO were higher when there were industrial areas in the neighborhood. This result is consistent with the results of previous studies [27,30,34,35,39,45]. Therefore, eco-friendly policies must be developed to transform existing factories into smart ones [87]. In particular, industrial areas are regions where many cargo trucks and heavy-duty diesel vehicles operate and factories emit air pollutants. Kim [88] reported the seriousness of the air pollutant emissions caused by diesel vehicles in Seoul. Generally, obligatory and continuous policies for the emission regulation of heavy-duty diesel vehicles operating in the city and the installation of DPFs are required.

The parks and green areas had a statistical significance only with $PM_{2.5}$ (coefficient = −0.132, p = 0.04). When there were more parks and green areas in the neighborhood, the concentration of $PM_{2.5}$ was lower. This result is consistent with those of the previous studies [28,31,52]. However, green areas can exhibit a negative correlation with all the air pollutants regardless of the statistical significance. This finding has implications on the impact of parks and green areas on the reduction of air pollution.

For the land development characteristics, when the total used surface of residential buildings in the neighborhoods was higher, the concentrations of CO (coefficient = −0.000, p = 0.03), NO_2 (coefficient = −0.000, p = 0.02), and PM_{10} (coefficient = −0.000, p = 0.02) were lower. However, Oh and Chung [58] examined a case study in Seoul and reported that when the density of residential buildings was higher, the concentrations of NO_2 and PM_{10} were higher. Therefore, these inconsistent research results, even for the studies in Korea, indicate that even cities in the same country should have different policies and programs for reducing air pollution. In this study, we subdivided the residential area buildings into single-family and multifamily houses. Interestingly, the concentrations of NO_2 (coefficient = 0.000, p = 0.00), PM_{10} (coefficient = 0.381, p = 0.00), and SO_2 (coefficient = 0.000, p = 0.00) were higher in neighborhoods with more single-family houses. Furthermore, multifamily housing did not have statistical significance. In general, single-family housing in Korea is an area where older buildings are denser than multifamily housing and is relatively poorly managed compared to multifamily housing. In Korea, which mainly uses Liquefied petroleum gas (LPG) and oil for indoor heating, air pollutants such as NO_2 and sulfur are likely to be discharged from sources such as old boilers existing in old single-family houses. These are the areas concentrated by the relatively socioeconomically vulnerable population. In fact, the high-poverty cluster in LA, USA, showed similar NO_2 and $PM_{2.5}$ concentrations compared to the low-poverty cluster; however, the concentrations of other pollutants were higher [89]. In addition, a study conducted in Montreal, Canada, found that NO_2 concentration was associated with the distribution of the low-income population [90]. Accordingly, it is necessary to consider replacing the old boilers in single-family houses and supporting the installation of boilers with low emission of air pollutants such as NO_2 and sulfur. Meanwhile, this result may suggest that in-depth research on the causes of air pollution in neighborhoods with more single-family houses rather than multifamily houses is required.

4. Conclusions

In this study, we examined the effects of the physical and socioeconomic characteristics of neighborhoods on the PM_{10}, $PM_{2.5}$, NO_2, CO, and SO_2 concentrations. A spatial regression analysis was conducted on the air pollution data of Daegu Metropolitan City, Korea's leading industrial city, for three years (from 2016 to 2018); the main results are as follows.

First, the socioeconomic characteristics considered in this study were not statistically significant regardless of the air pollutant types. However, from the perspective of an inclusive city, continuous research and focus are required to ensure that socially vulnerable groups, such as those aged below 15 years and above 65 years, and basic livelihood security recipients, are not environmentally disadvantaged.

Second, the effects of the built environment characteristics of the neighborhoods were different for each air pollutant. In particular, $PM_{2.5}$ was more affected by the built environment in comparison with other pollutants. Therefore, new policies and programs must address the reduction of air pollution for each air pollutant.

Third, when there were more main roads in the neighborhoods, the SO_2 concentration was found to be higher. Therefore, green spaces should be built along main roads to help prevent air pollution in these areas. The concentration of $PM_{2.5}$ was higher in the neighborhoods with more bus stops. Therefore, in the long term, outdated diesel buses need to be replaced by CNG buses or electric buses. Moreover, smoking needs to be prohibited at temporary stops and vehicle parking around bus stops.

Fourth, regarding the land-use characteristics, the concentrations of CO and $PM_{2.5}$ are likely to be high in industrial neighborhoods. This result suggests that the existing factory facilities need to be replaced by smart and eco-friendly factory systems, which need the support of the government. When the parks and green areas in the neighborhoods were larger, their positive impact on the air pollutant concentrations was reported to be greater. Specifically, for $PM_{2.5}$, the positive influence of the parks and green areas seemed to be significant. Therefore, air pollution concentration must be reduced, and places for improving the quality of life of people, such as rest areas, must be provided by constructing more parks and green areas.

Finally, when the total used surface of residential buildings was higher, the concentrations of the air pollutants were reported to be lower. Contextually, similar neighborhoods with more single-family houses tend to have high levels of air pollution. Therefore, because of the characteristics of the residential development system in Korea, single-family housing areas are likely to have fewer parks and green spaces than multifamily housing areas. This result suggests that more parks and green spaces should be considered in the urban redevelopment and regeneration of single-family housing areas.

Traffic volume and vehicle type can be expected to be significant factors affecting the concentration of air pollutants. However, this study could not examine the influence of these factors due to the lack of construction and management of traffic-volume and vehicle type at the local level in Korea. Moreover, urban climatological characteristics, such as precipitation, temperature, and wind, can be associated with the concentration of air pollutants. However, these characteristics could not be measured in this study because of the limited number of monitoring systems in Korea. Finally, the concentration of air pollutants and the factors affecting them are dependent on the characteristics of cities. Therefore, there is a need for continuous studies in various cities in Korea to improve their understanding. In addition, it is necessary to conduct a nationwide study and develop a policy in a large framework for reducing the concentration of air pollution in Korea. The significance of this study is expressed in examining the association between various air pollutants and the socioeconomic characteristics, as well as in the built environment of the neighborhoods. This study is expected to guide policymakers and planners in making smart decisions for eco-friendly and healthy cities.

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Appendix A

Table A1. Results of spatial regression models.

Classification		PM_{10}						$PM_{2.5}$					
		Ordinary Least Square (OLS)		Spatial Lag Model (SLM)		Spatial Error Model (SEM)		Ordinary Least Square (OLS)		Spatial Lag Model (SLM)		Spatial Error Model (SEM)	
		Coef.	t	Coef.	z	Coef.	z	Coef.	t	Coef.	z	Coef.	z
Socioeconomic characteristics	Children under 15	−0.072	−0.693	0.008	0.257	0.012	0.334	−0.004	−0.074	0.007	0.300	0.002	0.081
	Elderly above 65	−0.076	−0.728	0.005	0.165	0.039	1.011	−0.058	−0.876	0.008	0.348	0.020	0.713
	National basic livelihood security recipient	−0.041	−0.485	0.011	0.431	0.024	0.866	−0.056	−1.044	0.005	0.253	0.010	0.518
Road characteristics	Neighborhood street	0.023	0.812	0.002	0.230	0.001	0.127	0.029	1.670	0.006	0.989	0.002	0.348
	Main road	0.074 **	2.724	0.004	0.530	0.002	0.259	0.043 *	2.514	0.005	0.818	0.000	0.072
	Intersection	0.154	0.344	−0.099	−0.725	−0.131	−0.693	−0.668 *	−2.372	−0.197	−1.902	−0.254	−1.838
	Bus stop	0.246	0.415	0.073	0.404	0.119	0.644	0.613	1.638	0.278 *	2.0247	0.255	1.882
Land use characteristics	Housing area	−0.016	−0.748	−0.013 *	−2.017	−0.007	−0.988	−0.016	−1.172	−0.004	−0.881	0.001	0.200
	Commercial area	−0.048	−1.676	−0.017	−1.941	−0.009	−0.807	−0.049 **	−2.712	−0.015 *	−2.323	−0.007	−0.930
	Industrial area	0.997	1.008	0.504	1.661	0.581	1.518	0.959	1.540	0.453 *	1.984	0.559 *	1.995
	Park area	−0.651 *	−2.272	−0.160	−1.810	−0.165	−1.766	−0.383 *	−2.122	−0.132 *	−2.001	−0.093	−1.361
	Mixed use	1.688	0.635	0.503	0.617	0.415	0.548	−1.026	−0.613	−0.220	−0.359	−0.153	−0.276
Development density characteristics	Total used surface of residential buildings	−0.000 *	−2.280	−0.000 *	−2.229	−0.000	−1.073	−0.000 *	−2.434	−0.000	−1.176	−0.000	−0.345
	Total used surface of commercial buildings	0.000	0.700	0.000	0.419	0.000	0.501	0.000	0.632	0.000	0.563	0.000	0.457
	Single−family housing	1.242 **	2.973	0.381 **	2.963	0.193	1.626	0.633 *	2.406	0.138	1.430	0.029	0.337
	Multifamily housing	0.156	0.349	0.034	0.251	0.128	0.847	0.302	1.073	0.066	0.646	0.132	1.189
Rho				0.959 **	49.953					0.966 **	54.931		
Lambda (λ)						0.983 **	93.982					0.978 **	77.821
Robust LM lag		65.344 **						50.356 **					
Robust LM error		0.160						1.985					
Log likelihood		−348.35		−214.80		−221.66		−284.10		−175.92		−177.67	
N		139		139		139		139		139		139	
R^2		0.426		0.938		0.934		0.260		0.886		0.886	
Akaike information criterion (AIC)		730.71		465.60		477.32		602.21		387.85		389.35	
Schwarz criterion (SC)		780.59		518.42		527.21		652.10		440.67		439.24	

* $p < 0.05$, ** $p < 0.01$.

Table A2. Results of spatial regression models.

Classification		NO_2						CO						SO_2					
		OLS		SLM		SEM		OLS		SLM		SEM		OLS		SLM		SEM	
		Coef.	t	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z	Coef.	z
Socioeconomic characteristics	Children under 15	−0.000	−0.923	0.000	0.093	0.000	0.015	−0.000	−0.469	0.000	0.520	0.000	0.617	0.000 **	2.745	0.000	1.640	0.000	0.440
	Elderly above 65	−0.000	−0.161	−0.000	−0.406	−0.000	−0.144	−0.000	−0.665	−0.000	−0.206	0.000	0.461	0.000 **	2.684	0.000	1.315	0.000	0.739
	National basic livelihood security recipient	−0.000	−0.706	−0.000	−0.264	−0.000	−0.231	−0.000	−0.996	0.000	0.029	0.000	0.554	0.000	0.101	0.000	1.310	0.000	1.829
Road characteristics	Neighborhood street	0.000	1.556	0.000	0.766	0.000	0.692	0.000 *	2.546	0.000	1.705	0.000	1.431	0.000 **	3.281	0.000	1.645	0.000	0.237
	Main road	0.000 *	2.562	0.000	0.551	0.000	0.407	0.000 **	3.465	0.000	1.509	0.000	1.008	0.000 **	4.780	0.000 *	2.214	0.000	0.790
	Intersection	−0.000	−0.346	−0.000	−1.057	−0.000	−0.784	−0.000	−0.042	−0.001	−1.314	−0.002	−1.373	0.000	0.188	−0.000	−0.949	−0.000	−0.929
	Bus stop	0.000	0.389	−0.000	−0.225	−0.000	−0.150	0.005	1.181	0.002	0.167	0.002	1.545	0.000 *	2.113	0.000	1.865	0.000	1.240
Land use characteristics	Housing area	−0.000	−0.225	−0.000	−1.422	−0.000	−0.737	−0.000	−0.219	−0.000	−0.857	0.000	0.461	−0.000	−1.391	−0.000 *	−2.220	−0.000	−1.283
	Commercial area	−0.000	−0.577	−0.000	−0.864	−0.000	−0.529	−0.000	−0.449	−0.000	0.343	−0.000	−0.012	−0.000	−0.939	−0.000	−1.568	−0.000	−0.902
	Industrial area	0.001	1.951	0.000	1.666	0.000	0.913	0.015 *	2.035	0.006 *	2.196	0.005	1.542	0.000	0.931	0.000	1.739	0.000 *	2.032
	Park area	−0.000	−1.530	−0.000	−1.034	−0.000	−0.844	−0.004 *	−2.009	−0.001	−1.289	−0.000	−0.477	−0.000 *	−2.397	−0.000	−1.933	−0.000 *	−2.543
	Mixed use	0.001	0.660	0.000	0.449	0.000	0.215	0.021	1.086	0.007	0.920	0.004	0.609	0.000	0.407	0.000	0.452	0.000	0.317
Development density characteristics	Total used surface of residential buildings	−0.000	−1.891	−0.000 *	−2.199	−0.000	−1.951	−0.000	−1.875	−0.000 *	−2.067	−0.000	−1.867	−0.000 *	−2.568	−0.000	−1.906	−0.000	−0.950
	Total used surface of commercial buildings	0.000	0.572	−0.000	−0.000	0.000	0.222	0.000	0.625	0.000	0.016	0.000	0.206	0.000 *	2.383	0.000	1.615	0.000	1.206
	Single−family housing	0.000 *	2.470	0.000 **	2.950	0.000 *	2.241	0.005	1.617	0.002	1.920	0.001	1.528	0.000 **	3.348	0.000 **	3.287	0.000 *	2.430
	Multifamily housing	0.000	1.068	0.000	0.203	0.000	0.059	0.002	0.779	0.000	0.501	0.001	0.986	0.000	0.827	−0.000	−0.268	−0.000	−0.193
Rho				0.936 **	36.302					0.932 **	35.142					0.915 **	32.374		
Lambda (λ)						0.964 **	51.457					0.964 **	51.898					0.980 **	84.458
Robust LM lag		49.563 **						49.575 **						62.952 **					
Robust LM error		0.148						0.256						0.154					
Log likelihood		688.32		785.33		779.46		329.79		426.75		423.94		964.62		1061.94		1054.55	
N		139		139		139		139		139		139		139		139		139	
R^2		0.403		0.888		0.882		0.368		0.880		0.881		0.610		0.925		0.924	
Akaike information criterion (AIC)		−1342.64		−1534.66		−1524.93		−625.58		−817.51		−813.88		−1895.24		−2087.88		−2075.11	
Schwarz criterion (SC)		−1292.76		−1481.84		−1475.04		−575.69		−764.69		−763.99		−1845.35		−2035.06		−2025.22	

* $p < 0.05$, ** $p < 0.01$.

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