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The Effects of Bus Ridership on Airborne Particulate Matter (PM10) Concentrations

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Abstract: Air pollution caused by rapid urbanization and the increased use of private vehicles seriously affects citizens' health. In order to alleviate air pollution, many cities have replaced diesel buses with compressed natural gas (CNG) buses that emit less exhaust gas. Urban planning strategies such as transit-oriented development (TOD) posit that reducing private vehicle use and increasing public transportation use would reduce air pollution levels. The present study examined the effects of bus ridership on airborne particulate matter (PM10) concentrations in the capital region of Korea. We interpolated the levels of PM10 from 128 air pollution monitoring stations, utilizing the Kriging method. Spatial regression models were used to estimate the impact of bus ridership on PM10 levels, controlling for physical environment attributes and socio-economic factors. The analysis identified that PM10 concentration levels tend to be lower in areas with greater bus ridership. This result implies that urban and transportation policies designed to promote public transportation may be effective strategies for reducing air pollution.

Keywords: airborne particulate matter; bus ridership; air pollution; urban form; spatial model

1. Introduction

Many cities suffer from air pollution caused by rapid urbanization and the increased use of private vehicles [1,2]. Air pollution seriously affects citizens' health and causes various respiratory diseases [3–14]. According to the Organisation for Economic Co-operation and Development (OECD), the number of deaths attributable to air pollution rose by about 4% from 2005–2010, while the economic costs amounted to approximately 3.5 trillion US dollars annually [15]. The most commonly observed air pollutants include particulate matters (PM10 and PM2.5), ground-level ozone (O_3), carbon monoxide (CO), sulfur oxides (SO_2), nitrogen oxides (NO_2), and lead. The sources of these air pollutants include fuel combustion from vehicles, the burning of fossil fuels, industrial processes, and chemical reactions [16–19]. Amongst these, transportation represents the primary source of air pollutants, accounting for about half of all air pollutants emitted [20].

In Korea, urban air pollution is a serious problem, particularly in the capital region, where most of the country's population, industry, and traffic are concentrated. Between 2008 and 2010, the levels of NO_2 and PM10 in the capital region were higher than the OECD average [15]. While many factors influence air pollution (e.g., population, land-use, terrain, and wind direction), exhaust gases from vehicles (e.g., CO, NO_2, and PM10) are the main contributor in the capital region [11,19]. In order to alleviate air pollution, in 2000 the government of Seoul, as well as other local governments, began replacing diesel buses with compressed natural gas (CNG) buses, which emit less exhaust gas [21]. By 2015, every bus in Seoul was running on CNG, while about 80% of buses in other cities in the capital region had been converted [22].

Urban planning strategies, such as transit-oriented development (TOD), posit that decreased private vehicle use and increased public transportation use would reduce air pollution levels [11,19,23–27]. TOD relies on a mixed-use residential and commercial design to maximize access to public transport [23]. A TOD neighborhood typically has a center with a transportation node (e.g., train station, metro station, or bus station) [23,28]. TOD projects generally encompass a one-quarter to one-half mile radius from a transportation node; this is considered an appropriate scale for pedestrians [29]. While many studies have investigated the effects of TOD, few have empirically evaluated the impact of transit ridership on air pollution. Thus, in this study we examined the relationship between bus ridership and airborne particulate matter (PM10) concentration levels, interpolating the level of PM10 from 128 air pollution monitoring stations in the capital region of Korea with the expected objective of providing valuable insight into effective and sustainable urban and transportation polices for alleviating air pollution.

We used bus traffic as an explanatory variable and socio-economic factors as control variables. We also utilized environmental variables that affect traffic and air flow—through street-canyon effects—such as intersection density, building coverage ratio, and land-use diversity. These variables controlled for the effects of urban geometry related to the dispersion of PM10 [30,31]. In addition, approximately half of the PM10 observed in Korea originates from China and is transferred over the Yellow Sea, which is located between China and Korea [32]. Thus, we used a variable that measures the distances between the administrative districts in the region and the Yellow Sea to account for the effect of air pollutants emitted from China, which is one of the most significant problems in Northeast Asia [32,33]. The rest of this paper consists of a review of relevant theories and empirical studies, an introduction to the study settings and methods, an analytical report of the results, and a discussion of those results.

2. Background

Calthrope, an American architect and planner, was the first to propose TOD [23], which strives to build public transportation and pedestrian-friendly environments to reduce automobile use, thereby alleviating pollution, excessive energy consumption, and the destruction of green areas. Many cities (especially American cities) have since incorporated the TOD concept, and many references to TOD can be found in institutional reports and journals [23]. Some TOD-related studies have investigated factors influencing travel behavior (e.g., private vehicle use, transit ridership, walking, and biking). Focusing on bus ridership, Cascajo et al. [34] investigated variables that affected the use of this transport method in Spanish cities. Their spatial error model detected significant effects of urban surfaces, population density, and the length of the bus network on bus ridership, finding that the distance travelled by bus per person decreased with the existence of a metro system in the city; thus, these researchers concluded that bus and metro transportation systems are not complementary but rather compete with each other.

Chakraborty and Mishra [35] attempted to establish the relationship between transit ridership and land use variables using ordinary least-squares (OLS) and spatial error modelling (SEM), classifying the state of Maryland, USA, into urban, suburban, and rural areas; their results showed that determinants and coefficients varied across the three area types. These researchers also found that land-use type, density, transit accessibility, and income strongly correlated with transit ridership. Thompson et al. [36] analyzed the transit demand for work travel in Broward County, Florida, identifying the following factors that improved transit ridership: mixed land use, greater walkability, and, especially, easy access to employment. To increase transit ridership, these researchers suggested facilitating direct transit links and linking riders to employment centers using multi-destination transit network structures.

Other literature has sought to identify the effects of urban spatial structures on air pollution through several methods. Such studies have widely used spatial interpolation methods (e.g., Kriging, IDW (Inverse Distance Weighting), nearest neighbor, and spatial averages) to construct new data points within the range of a discrete set of known data points. Among these, the Kriging method appears to be more realistic and less biased than other methods [37].

Ross et al. [38] used the land use regression (LUR) model developed by Briggs et al. [39]. The LUR model is one of the most widely used exposure assessment tools in air pollution epidemiological research to estimate pollutant concentrations at unmonitored locations. The LUR model evaluates the relationship between observed air pollution concentrations and predictor variables (e.g., land use and traffic conditions) around monitoring sites, following a multivariate regression model. Researchers generally construct these predictor variables using a Geographic Information System (GIS). Ross et al. estimated nitrogen dioxide (NO_2) concentration levels in southern California using the LUR model, with traffic in a 300–1000-m buffer zone, road length in a 40-m buffer zone, and distance to the coast serving as key variables. These researchers found that road length and traffic were positively correlated with NO_2 levels. Few previous studies had considered wind or coastal effects, but their study identified a coastal effect on air pollution.

Oh and Chung [40] estimated the influence of urban development density on air pollution in Seoul, Korea. Their model included development factors such as population, employee density, land use, the number of buildings, and traffic. These researchers identified a correlation between changes in development density and air pollution levels.

Jerrett et al. [41] used the LUR model to analyze the relationship between air pollution levels and the built environment in Toronto, Canada. Their model included variables grouped into five categories: land use, roads and traffic, population, physical geography, and meteorology. Their analysis identified road density as the most influential factor on NO_2 levels, being related to traffic demands. Hence, as lower mixed land use tends to increase vehicle traffic demands, this study indicated that increased mixed land use could reduce traffic demands.

Kim [42] estimated the effects of urban structure factors on CO_2 concentrations. In his study, Kim grouped 72 Korean cities into four different types: monocentric-centralized cities, polycentric-centralized cities, monocentric-decentralized cities, and polycentric-decentralized cities. Among the four types, the study found that CO_2 levels tended to be lowest in monocentric-centralized cities (e.g., Wonju-si). The study also identified high density and mixed development as having lower levels of CO_2 concentrations. Kim and Jun [43] analyzed air pollutants in the capital region of Korea, classifying it into the city centers, satellite cities, and suburbs. Particulate matter levels were highest in the suburbs and lowest in the city centers. Their study also found that distance from the Han River and the Yellow Sea was a statistically significant predictor of CO_2 concentrations.

While researchers have conducted many studies related to air pollution in the fields of urban and transportation planning, few studies have explored the effects of transit ridership on air pollution. Although the TOD literature suggests that the promotion of public transit can reduce air pollution, there is insufficient empirical research on the relationship between the level of public transit use and air conditions. Therefore, the present study tested the effects of transit ridership on air pollution, focusing on PM10 levels in the capital region of Seoul, Korea (where clean CNG buses widely operate). Because transportation represents the primary source of PM10 concentrations, we expected higher levels of bus ridership, through traffic reduction, to be correlated with lower PM10 concentrations [20].

3. Method

3.1. Context

The capital region of the Republic of Korea contains three different administrative districts: Seoul, Incheon, and Gyeonggi-do. As of 2015, this region covered about 11,704 km^2, with a population of approximately 25.5 million. Although geographically it represents only 12% of Korea, approximately half of the country's population, manufacturing, and service industries are concentrated in the capital region. Moreover, 68% of deposits and 86% of public institutions are situated in this region, which serves as the Korean center of administration, finance, and industry.

Among the three districts, Seoul is the center of the capital region. It is the capital and the largest metropolis in South Korea. One of the densest and the largest cities in the world, Seoul is home to 10.1 million citizens (as of 2015) within its 605.3 km^2 boundary, with a population density of around 16,700 persons/km^2. The city has one of the most advanced public transportation systems in the world. As of 2015, 10 subway lines (excluding national railways) and 598 bus lines were operating within Seoul. The city's bus system, which was reorganized in 2004, connects destinations that are inaccessible by subway. A median bus corridor plays a particularly important role in enhancing the system's efficiency.

3.2. Data and Key Variables

The descriptive statistics of the key variables are shown in Table 1. Administrative districts served as the unit of analysis. In air pollution studies, PM10 refers to particles smaller than 10 μm [44]. We used the data that include hourly PM10 concentration levels at 128 air pollution monitoring stations in the capital region (Figure 1), which were provided by the National Institute of Environmental Research, South Korea. In Korea, the beta-ray absorption method is the standard instrument for PM10 concentration measurement [45]. Hourly PM10 concentrations are obtained from measuring the increase in beta-ray absorption through particles collected on the filter paper. The principle of the beta-ray absorption method is that the beta-ray absorption rate increases in proportion to the mass of the PM10 on the filter. The beta-ray absorption method can be incorporated into an automatic measurement system. However, because the beta-ray absorption method requires approximately one hour to collect PM10, real-time measurement is impossible. Also, PM10 concentration measurement using the beta-ray absorption method is influenced by the relative humidity of the area [46].

Table 1. Descriptive statistics (n = 1097).

	Variable	Mean	Std. Dev.	Min	Max
Outcome Variables	PM10 (μg/m^3)	55.515	3.587	49.271	67.436
Traffic Variables	Bus Traffic	18,101.47	13,481.31	77.765	145,423.3
	ln (Bus Traffic)	9.507	0.916	4.354	11.887
	Total Traffic	102,541.2	72,559.18	683.055	784,550.3
	ln (Total Traffic)	11.299	0.783	6.527	13.573
Socio-economic Variables	Population Density (1000 persons/km^2)	15.754	13.375	0.002	56.112
	Employee Density (1000 persons/km^2)	5.037	7.829	0.000	90.510
	Ratio of Manufacturing Employees (%)	1.994	5.043	0.000	87.576
Environmental Variables	Administrative District Area (km^2)	10.872	22.816	0.185	246.956
	Power Plant (dummy)	0.006		0.000	1.000
	Intersection Density (unit/m)	8.133	4.995	0.642	26.457
	Park Density (%)	0.096	0.147	0.000	0.847
	Building Coverage Ratio (%)	0.164	0.124	0.000	0.524
	Land Use Diversity	0.443	0.139	0.000	0.854
	Green Belt (dummy)	0.174		0.000	1.000
	Distance from Yellow Sea (km)	66.979	18.039	0.000	136.101

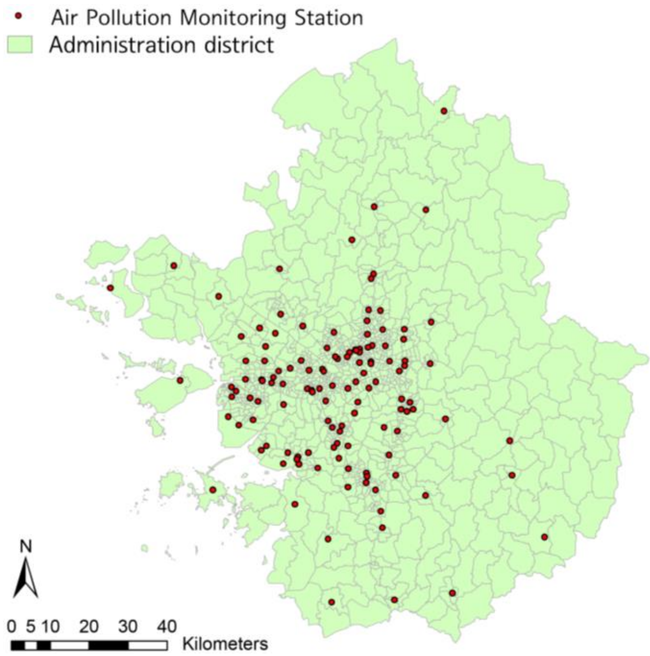

Figure 1. Air pollution monitoring stations.

The air pollution monitoring stations are categorized into three groups (104 urban stations, 20 roadside stations, and 4 suburban stations) by the Ministry of Environment, South Korea. The PM10 monitoring stations in the capital region are clustered in the western portion of the region, covering the administrative areas in which the population is concentrated. There are fewer stations located on the peripheries of the region, where there is a relatively low population density. We calculated the annual average PM10 level at each station. A possible problem is that PM10 concentration levels at roadside monitoring stations tend to be higher than the values at other types of stations due to PM10 emission from traffic. However, the extent to which roadside stations inflate PM10 concentration levels relative to other station types is unclear. After conducting a sensitivity analysis (Table 1) (we conducted a sensitivity analysis that applied weights (0.9, 0.8, 0.7, 0.6) to PM10 values at roadside stations. Table 1 shows that the effects of bus traffic remained significant at the 0.05 alpha level when weights of 0.9 and 0.8 were applied, became significant at the 0.10 level when a weight of 0.7 was applied, and disappeared with a weight of 0.6. The effect of employment density became insignificant when a weight of 0.7 was applied. The effects of total traffic, ratio of manufacturing employees, and distance from the Yellow Sea remained significant regardless of the weights. Overall, the estimates were stable until applying weights of 0.8 to values at roadside monitoring stations), we decided to estimate PM10 concentration levels without weights according to the three categories and spatial distribution of the stations, following previous studies that used the same data source [37–39].

Because PM10 levels were measured at only 128 monitoring stations, no PM10 data was available for many administrative areas. We estimated PM10 concentration levels at unobserved locations utilizing the Kriging method (Figure 2). The Kriging method of interpolation weights observed surrounding data points according to spatial covariance values, thus predicting values for unmeasured locations. Hence, the PM10 concentration levels for the whole capital region were estimated from the data observed at the monitoring stations. Because the administrative district served as the unit of analysis, we calculated the average PM10 value for each district (Figure 3). As seen in Table 1, the average PM10 concentration level in 2010 in the capital region was 55.5 $\mu g/m^3$, which is much higher than the World Health Organization's guideline (20 $\mu g/m^3$). This value shows how serious the PM10 problem is in the region.

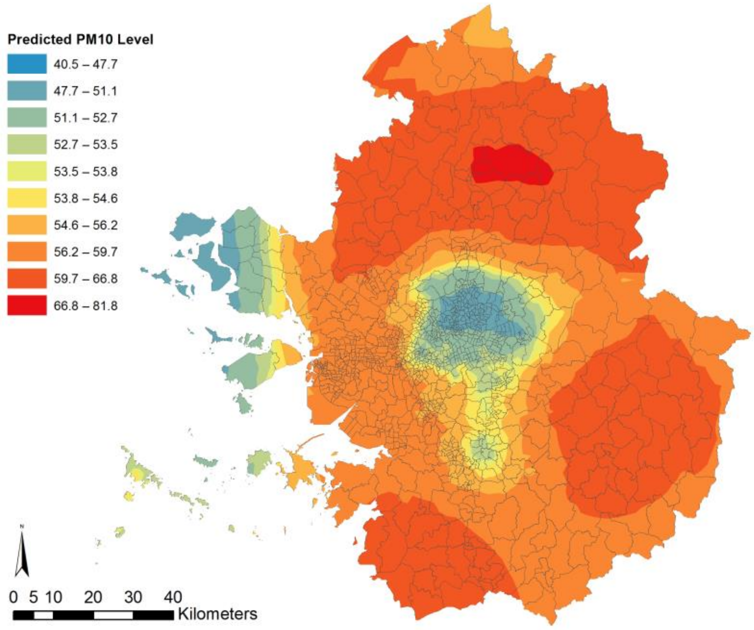

Figure 2. The level of airborne particulate matter (PM10) utilizing Kriging.

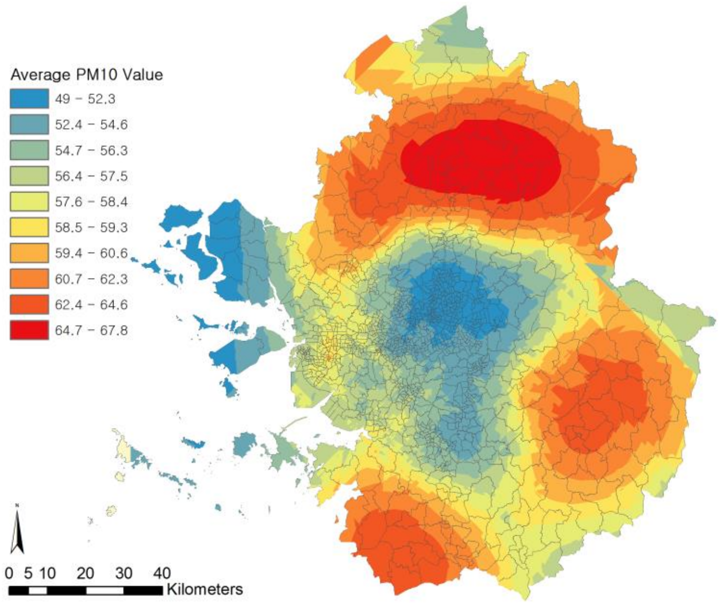

Figure 3. The average PM10 value within the administration districts.

In order to construct variables that captured traffic, socio-economic factors, and environmental attributes, the present study combined data from the household travel diary survey with Korean GIS data (Table 1). We based the traffic variable on the household travel diary survey, comprising primary transport O/D (Origin/Destination) data. The total bus traffic variable estimated the number of bus riders (including ingressing and egressing riders) on a regular route, as well as on other types of buses. The bus system is one of the major transportation modes in the region: the average bus traffic value was 18,101.47, representing approximately 17% of total traffic (102,541.2) (Table 1). We expected the PM10 levels in administrative districts with more bus riders to be lower—as CNG buses emit little PM10—because high levels of bus ridership imply less automobile use, which produces PM10. The total traffic variable encompassed the total number of riders via nine primary transport modes: pedestrian/bike, freight/other, bus on a non-regular route, rail, private vehicle, taxi, bus, subway, and subway/bus. We included the total traffic variable to control for the effect of overall traffic on PM10 levels. We adapted the traffic variables to natural log-transformations, as both bus traffic and total traffic distributions were positively skewed.

Socio-economic factors (e.g., population density and employee density) measured overall activity levels in the administrative districts. The ratio of manufacturing employees indicated the concentration of manufacturing industries; therefore, we expected districts with high manufacturing employee ratios to have high PM10 levels, assuming that manufacturing industries emit relatively higher levels of pollutants. A power plant and a green belt served as dummy variables. We expected a district with a power plant to have high PM10 levels due to the pollutants emitted by the power plant. We expected a district with a green belt to have low PM10 levels due to the lack of facilities emitting pollutants. We anticipated a negative relationship between the park density variable and PM10 levels because parks tend to mitigate air pollution.

We generated factors expected to affect bus ridership according to TOD theory (e.g., intersection density, building coverage ratio, and land use diversity) using the road name address base map in GIS. These urban geometries influence not only urban activities but also the dispersion of PM10 through the street-canyon effect [30]. We constructed a variable that denotes the distance from the Yellow Sea in order to identify the effect of serious air pollution from China. Air pollutants from China influence air quality in Korea through westerly winds [33]. This variable was measured as the value of the X-coordinate, setting the westernmost administration district as the origin.

3.3. Spatial Regression Model

Spatial regression models were used to estimate the impact of bus ridership on PM10 levels, controlling for physical environment attributes and socio-economic factors. Air pollution data with spatial attributes were influenced by spatial autocorrelation, which involves correlating one value of a single variable with other nearby values [47,48]. The spatial autocorrelation of PM10 can be observed in Figure 2; districts with low PM10 levels tend to cluster with other low PM10 districts, and high PM10 districts also tend to cluster together. When spatial autocorrelation exists, a regression model of OLS lacks credibility, as it violates the independent residuals assumption of OLS. We used Moran's I to verify spatial autocorrelation [49,50]. Moran's I for PM10 levels was 0.63, reaching statistical significance ($p = 0.000$) and confirming the existence of visually observed spatial autocorrelation.

Having identified spatial autocorrelation, SEM and the spatial lag model (SLM) can control for spatial autocorrelation using a spatial weight matrix, overcoming the limits of OLS [47]. SLM assumes that spatial autocorrelation occurs in the observed values of individual dependence variables and thus controls for spatial autocorrelation by applying the spatial weight matrix (ρWy) to observed close values that affect each observed value [48].

$$y = \rho Wy + x\beta + \varepsilon$$

y: dependent variable vector; W: spatial weight matrix; x: independent variable matrix; ρ, β: coefficients; ε: independent and identically distributed residual vector.

SEM assumes that residuals include spatial autocorrelation that occurred in the unobserved values of individual dependence variables and thus controls for spatial autocorrelation by applying the spatial weight matrix to close residuals that affect each residual.

$$y = x\beta + \varepsilon,\ \varepsilon = \lambda W + \mu$$

y: dependent variable vector; W: spatial weight matrix; x: independent variable matrix; λ, β: coefficients; ε: spatial-dependent residual vector; μ: independent and identically distributed residual vector.

The present study used spatial regression models to estimate the impact of bus ridership on PM10 levels, controlling for physical environment attributes and socio-economic factors. We estimated the models using GeoDa, a spatial analysis program.

4. Analysis Results

The present study first used the OLS regression model to select suitable spatial regression models with which to estimate PM10 levels (Model 1 in Table 2). When spatial autocorrelation existed, we selected the more suitable model between SLM and SEM by utilizing the robust Lagrange Multiplier (LM) test. The results indicated that, while both SLM and SEM were superior to OLS, SEM was more suitable due to its larger robust LM value [48]. Thus, the present study used SEM (Model 2 in Table 2). The significant Lamda (λ) value also indicated that SEM was more suitable than OLS. Further, the examination of residuals indicated that SEM successfully accounted for spatial autocorrelation (Moran's I = 0.036, Figure 4). The application of a spatial weight matrix in the SEM model notably increased the R-squared value and changed the significance levels of some variables. The OLS model detected statistically significant effects of explanatory variables (e.g., population density, administrative district area, intersection density, park density, building coverage ratio, and green belt). However, these effects vanished in the SEM model after controlling for spatial autocorrelation.

Table 2. Ordinary least-squares (OLS) and spatial error modelling (SEM) results for PM10 estimation.

Variable	Model 1: OLS		Model 2: SEM	
	Coef.	(S.E.)	Coef.	(S.E.)
Coefficient	52.911 ***	1.583	48.337 ***	0.508
ln (Bus Traffic)	−1.520 ***	0.249	−0.240 **	0.080
ln (Total Traffic)	1.730 ***	0.287	0.509 ***	0.091
Population Density (1000 persons/km^2)	−0.057 ***	0.011	0.000	0.003
Employee Density (1000 persons/km^2)	−0.117 ***	0.014	−0.015 ***	0.004
Ratio of Manufacturing Employees (%)	17.207 ***	2.636	4.878 ***	1.205
Administrative District Area (km^2)	0.030 ***	0.005	−0.002	0.002
Power Plant (dummy)	−1.634	1.035	−0.166	0.297
Intersection Density (unit/m)	−0.230 ***	0.029	0.001	0.010
Park Density (%)	−2.649 ***	0.640	−0.151	0.192
Building Coverage Ratio (%)	6.517 ***	1.600	0.147	0.476
Land Use Diversity	0.367	0.678	0.077	0.193
Green Belt (dummy)	−0.729 **	0.250	0.068	0.080
Distance from the Yellow Sea (km)	−0.011 **	0.006	0.031 **	0.011
Lamda (λ)			0.998 ***	0.002
R-Squared	0.439		0.951	
n	1097		1097	
Robust LM (lag)	149.115 ***			
Robust LM (error)	2258.293 ***			

Note: ** $p < 0.01$; *** $p < 0.001$.

The results of the SEM model supported our hypothesis that the level of PM10 concentration is correlated with bus ridership. In the SEM model, the effect of bus traffic was statistically significant ($p = 0.003$). The negative and significant coefficient of log-transformed bus traffic indicated that the higher the bus traffic in a district, the lower the PM10 levels. The total traffic variable accounted for the influence of overall traffic on PM10 concentrations because vehicles are the major source of PM10: the positive coefficient of total traffic shows that, as expected, PM10 levels tended to be higher in districts with higher total traffic ($p < 0.000$). The results regarding the two traffic variables showed that while greater traffic is likely to produce more PM10, greater bus traffic tends to mitigate PM10 concentrations.

Among the districts' socioeconomic factors, the effects of employment density and the ratio of manufacturing employees were statistically significant: PM10 levels were likely to be lower in districts with higher employee density (p = 0.001) but higher in districts with a high proportion of manufacturing employees (p < 0.000). Because the ratio of manufacturing employees captures manufacturing industry concentrations, this result demonstrated the influence of secondary sector industries on PM10 levels.

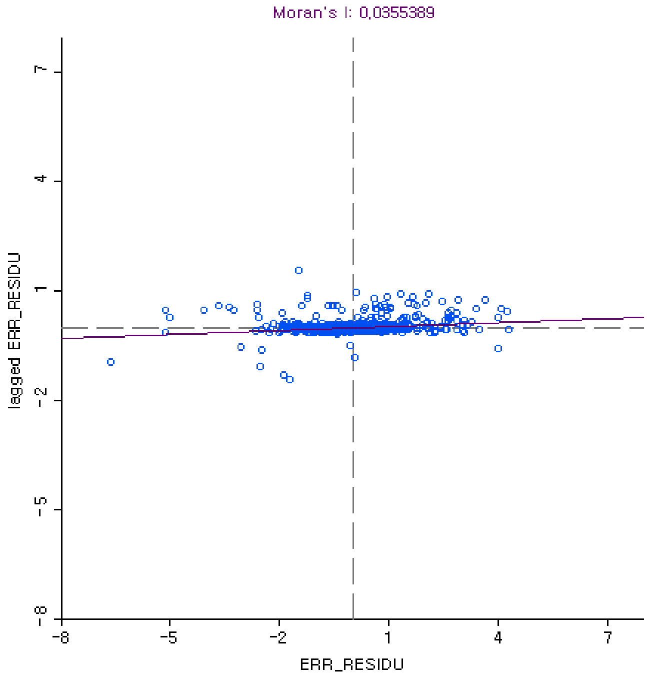

Figure 4. Moran's I of SEM's residual.

The effects of environmental variables including administrative district area, intersection density, park density, building coverage ratio, and green belt—which were significant in the OLS model—became insignificant in the SEM model, implying the spatial dependency of PM10 distribution. However, distance from the Yellow Sea remained significant (p = 0.006), even after controlling for the spatial autocorrelation of PM10 concentrations: the farther a location was from the Yellow Sea, the lower its PM10 concentration levels. This result indicated the effect of PM10 influx from China across over the Yellow Sea.

5. Conclusions

The rapid pace of urbanization and increased personal vehicle use has given rise to various urban problems (e.g., traffic congestion and air pollution). These problems have resulted in social costs and have negatively influenced the quality of citizens' lives. In particular, air pollution exacerbates health conditions, causing various respiratory diseases. The OECD reported the seriousness of air pollution in 2014, and a number of international organizations (e.g., the United Nations) have endeavored to reduce air pollution.

Korea suffers from severe air pollution. The capital region of Korea, in particular, has experienced serious negative effects from air pollution. Transportation is one of the major contributors to this pollution. Hence, the Korean government has endeavored to reduce air pollution by enacting policies encouraging public transportation use and the replacement of diesel buses with CNG buses.

While transportation factors appear to be important for reducing air pollution, few studies have empirically evaluated the impact of transit ridership on air pollution. Instead, most studies have investigated the impact of urban forms on air pollution or on transit ridership. The present study is significant in that we analyzed the effects of the use of buses—a major mode of transportation, yet rarely investigated—on PM10 levels. We used SEM to test the influence of bus traffic on PM10 levels, accounting for the spatial autocorrelation of the distribution of PM10 concentrations.

Our model identified a correlation between bus traffic (the estimated number of bus riders, including ingressing and egressing riders) and PM10 levels. The results indicate that districts with higher bus traffic are likely to have lower PM10 levels. Additionally, the total amount of traffic was positively correlated with PM10 levels, indicating that transportation is a major source of PM10 concentrations. Considering these two effects, CNG buses, which emit very little PM10, may have replaced many private vehicles that emit air pollutants, leading to decreased PM10 levels. The fact that bus traffic positively affects air quality supports the effectiveness of Korea's transportation policy that replaced diesel buses with CNG buses in the capital region. In addition, the results suggest the benefits of urban planning strategies, for example, TOD, which promote public transportation use, thereby alleviating air pollution.

The negative effect of employment density on PM10 levels is somewhat unexpected. A possible explanation for this may be that most employees in the capital region are working in the tertiary sector, which produces less PM10 relative to secondary sector industries. Related to this, a higher ratio of manufacturing employees correlated to higher PM10 levels. Finally, the results demonstrate that PM10 concentrations increase as proximity to the Yellow Sea increases, indicating the influence of PM10 influx from the west.

Despite the significance of these findings, the results should be interpreted carefully, as our study only included 128 air pollution monitoring stations. The three types of stations (urban area, roadside, and suburban) could be a source of bias because PM10 levels on roadsides tend to be higher than those in urban areas due to pollutants from traffic. The location of these monitoring stations is also biased toward the western side of the capital region, reflecting the distribution of the population and industry, which may lead to less reliable estimation of PM10 concentrations in eastern areas. Although the Kriging method is widely used for deriving unobserved values from observed values, this interpolation process contains an inherent limitation in that the predicted values ultimately differ from the actual values. Further, we did not consider certain factors that affect air pollution (e.g., wind and seasonal changes) in this study due to a lack of sufficient data.

To improve the measurement and estimation of PM10 concentrations, a larger number of monitoring stations in a consistent context (e.g., roadside) is essential. Through the development of information and communication technology, wireless PM10 sensors are now available. Our future studies will monitor PM10 and other air pollutants using these wireless sensors, more reliably revealing factors that affect air pollutant concentrations. Despite these limitations, the present study empirically identified the influence of bus ridership on PM10 concentrations. Future studies utilizing more detailed factors and more reliable interpolation methods could improve the reliability of this investigation, thereby contributing greater insights for healthy urban and transportation planning.

To summarize, despite its uncertainties, the present study identified a relationship between higher bus traffic and lower PM10 concentrations. Thus, the analysis offers an initial result that can contribute to the formulation of traffic policies for air quality improvement. Moreover, the results suggest that urban and transportation policy aimed at promoting public transportation can be an effective approach to reducing air pollution. Thus, governments need to encourage citizens to use public transportation while also preparing support systems (e.g., median bus corridor systems, convenient transfer systems, and arrival information systems) to invigorate their public transportation systems.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix

Table 1. Sensitivity analysis result of SEM models weighting monitoring stations at roadside.

Variables	Road 1.0	Road 0.9	Road 0.8	Road 0.7	Road 0.6
	Coef. **(S.E.)** ***p*-Value**	**Coef.** **(S.E.)** ***p*-Value**	**Coef.** **(S.E.)** ***p*-Value**	**Coef.** **(S.E.)** ***p*-Value**	**Coef.** **(S.E.)** ***p*-Value**
Coefficient	48.337 *** (0.531) 0.000	47.075 *** (0.631) 0.000	47.197 *** (0.635) 0.000	48.218 *** (0.587) 0.000	49.301 *** (0.571) 0.000
ln (Bus Traffic)	−0.240 ** −0.081 0.003	−0.229 * −0.096 0.017	−0.209 * −0.097 0.03	−0.168 −0.089 0.061	−0.143 −0.087 0.1
ln (Total Traffic)	0.509 *** −0.092 0.000	0.529 *** −0.11 0.000	0.492 *** −0.111 0.000	0.398 *** −0.102 0.000	0.317 *** −0.099 0.000
Population Density (1000 persons/km^2)	0.000 −0.003 0.918	0.000 −0.004 0.918	−0.001 −0.004 0.816	−0.001 −0.004 0.879	0.000 −0.004 0.922
Employee Density (1000 persons/km^2)	−0.015 *** −0.005 0.001	−0.013 * −0.005 0.012	−0.011 * −0.005 0.042	−0.007 −0.005 0.16	−0.003 −0.005 0.591
Ratio of Manufacturing Employees (%)	4.878 *** −1.221 0.000	5.847 *** −1.451 0.000	5.923 *** −1.461 0.000	5.027 *** −1.351 0.000	3.033 * −1.313 0.021
Administrative District Area (km^2)	−0.003 −0.002 0.128	−0.002 −0.002 0.3	−0.002 −0.002 0.422	0 −0.002 0.916	0.001 −0.002 0.596
Power Plant (dummy)	−0.166 −0.301 0.58	−0.324 −0.358 0.366	−0.203 −0.36 0.573	−0.085 −0.333 0.798	0.159 −0.324 0.624
Intersection Density (unit/m)	0.001 −0.01 0.937	−0.001 −0.012 0.926	−0.005 −0.012 0.686	−0.009 −0.011 0.435	−0.012 −0.011 0.251
Park Density (%)	−0.151 −0.194 0.437	−0.280 −0.231 0.225	−0.177 −0.232 0.447	−0.012 −0.215 0.957	0.193 −0.209 0.356
Building Coverage Ratio (%)	0.147 −0.481 0.76	0.116 −0.572 0.839	0.225 −0.576 0.696	0.309 −0.532 0.561	0.464 −0.517 0.369
Land Use Diversity	0.077 −0.196 0.696	0.037 −0.233 0.872	0.076 −0.234 0.746	0.132 −0.216 0.543	0.155 −0.21 0.461
Green Belt (dummy)	0.068 −0.08 0.398	0.083 −0.096 0.384	0.102 −0.096 0.29	0.113 −0.089 0.205	0.112 −0.086 0.196
Distance from the Yellow Sea (km)	0.031 ** −0.011 0.006	0.027 * −0.013 0.043	0.026 −0.013 0.054	0.029 * −0.012 0.021	0.032 ** −0.012 0.008
Lamda (λ)	0.998 *** −0.002 0	0.998 *** −0.001 0	0.998 *** −0.001 0	0.999 *** −0.001 0	0.999 *** −0.001 0
n	1097	1097	1097	1097	1097

Note: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

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