




Article

Effectiveness of Particulate Matter Forecasting and Warning Systems within Urban Areas

Yeeun Shin ¹, Suyeon Kim ² , Jinsil Park ¹, Sang-Woo Lee ¹  and Kyungjin An ^{1,*} 

¹ Department of Forestry and Landscape Architecture, Konkuk University, Seoul 05029, Korea; julie9276@konkuk.ac.kr (Y.S.); jinsil4877@konkuk.ac.kr (J.P.); swl7311@konkuk.ac.kr (S.-W.L.)

² Rural Environment & Resource Division, National Institute of Agricultural Sciences, Wanju-gun 55365, Korea; mdl94@korea.kr

* Correspondence: dorian@konkuk.ac.kr

Abstract: The close relation between atmospheric pollution and human health has been well documented. Accordingly, various policies have been enacted worldwide to reduce and regulate air pollution, with most countries having established correlated monitoring systems. Notably in South Korea, increasing concerns about particulate matter (PM) concentrations led to the establishment of a nationwide forecasting and warning system in 2014. In this study, the PM trends in South Korea over the past decade were examined, and the correlated social issues were analyzed. In addition, the relationships between PM concentration, the forecasting–warning system, and people’s urban park use were analyzed to assess the efficacy of policy introduction. The results indicated that PM concentrations were an obstacle to outdoor activities, and the PM forecasting–warning system affected urban park use. Whereas the effects of PM forecasting and warning systems have not been sufficiently explored in practical terms in the literature, this study could be significant in proving the validity of environmental policies through the evidence including urban park visitors. This study also suggests future directions for developing PM forecasting and warning systems.

Keywords: particulate matter; PM forecasting; PM warning system; urban park; visitation; big data



Citation: Shin, Y.; Kim, S.; Park, J.; Lee, S.-W.; An, K. Effectiveness of Particulate Matter Forecasting and Warning Systems within Urban Areas. *Sustainability* **2022**, *14*, 5394. <https://doi.org/10.3390/su14095394>

Academic Editor: Alessandra De Marco

Received: 14 March 2022

Accepted: 27 April 2022

Published: 29 April 2022

Publisher’s Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Atmospheric pollution can influence citizens’ decision making regarding outdoor activities via multiple paths, including visual or detrimental health effects [1–5]. Over the past decade, interest in air pollution has steadily increased, and the World Health Organization (WHO) has classified air pollution as the greatest risk factor for human health [6,7]. Particulate matter (PM, including PM₁₀ and PM_{2.5}) has a more lethal effect on humans, owing to its small size [8,9]. PM originates from various natural and artificial sources, such as forest fires, traffic, and industrial activities [10–12]. Furthermore, PM can remain airborne for extended periods, owing to its small size. When humans are exposed to high concentrations of PM-containing chemical components, serious health issues can occur, such as heart disease, asthma, and respiratory tract illness, all of which can decrease life expectancy [9,13–15].

In addition to its direct effect on human health, PM has a negative effect on visibility, as it scatters light, and this effect worsens at higher concentrations (e.g., smog) [16]. Accordingly, low visibility affects peoples’ decisions and willingness to participate in outdoor activities [17]. As such, air pollution, including PM, has negative impacts on various aspects of well-being. Therefore, a great number of countries have established relevant policies to improve overall air quality. Air pollution is also effectively controlled and monitored, and such information is readily available to the general public. Furthermore, various means of monitoring and predicting air pollution trends are being developed.

Particularly in South Korea, the issue of PM has gained popularity relatively rapidly since 2014. Accordingly, various PM-related policies have been enacted, including the

Special Act on Particulate Matter Reduction and the PM Forecasting and Warning System. In the present study, we aimed to analyze changes in the perception of PM in South Korea and to determine how the implementation of PM concentration forecasting and warning systems has affected people's outdoor activities.

2. Literature Review

Various studies have shown that air pollution affects decision making regarding outdoor activities [1–4,12]. For example, Roberts et al. [2] showed that increasing air pollution concentrations decreased people's physical activity in the US, whereas Xu et al. [3] studied the relationship between air pollution and travel behavior, revealing that the greater the degree of air pollution, the lower the number of travel area visited and distance traveled. Notably, the correlation pattern with PM concentrations did not differ, owing to levels of concern regarding the correlated health issues and visual effects of PM [12,18]. Similarly, An et al. [4] found that an increase in PM concentrations was correlated with a decrease in physical activity time.

As such, air pollution is closely related to human health and activity, with the associated risks having been emphasized in numerous studies. For example, the WHO noted that nation states should directly provide air pollution information (including PM) to their populace to ensure that individuals are informed [19] and can determine their actions based on this information [20]. Accordingly, to identify the precise degree of air pollution and prepare appropriate countermeasures, countries around the world are monitoring air pollution. In addition, the public can easily access air quality information for major cities around the world in real time. Various air quality maps have been built, and the UN Environment Programme built an urban air action platform to provide air quality data, including information about wildfires, monitoring points, and wind information (<https://www.unep.org> accessed on 17 January 2022).

Recent studies related to PM monitoring have focused on predicting air pollution and increasing prediction accuracy based on accumulated data [17,20–22]. One such study was conducted in China to establish a model to identify and predict the interactions of air pollution sources [7], with the underlying purpose of developing an air quality early warning system for predicting harsh atmospheric conditions to allow for early actions against air pollution. Additionally, Balram et al. conducted a study to predict the concentration of PM_{2.5} based on air pollution data collected in Zuoying, Taiwan [20]. Within the study, the derived results were used for modeling the air quality warning system. For each method, Bayesian regularized neural network via forward feature selection system (BRNN/FFS) and support vector machine classifier were used. Similarly, a study was carried out in Australia attempting to increase the accuracy of air quality prediction models using an online sequential extreme learning machine (OS-ELM) [21]. As artificial intelligence technology advances, the current research is trending toward building a system for air pollution prediction based on accumulated data.

Air pollution information has also been used as the basis for policy formation, with Canada, the US, and China all implementing PM forecasting systems [23]. Similarly, the government in South Korea has implemented a PM forecasting and warning system, where during periods of poor air quality, necessary information on recommended actions is provided directly to citizens.

Through such policies, citizens have gained access to various types of daily PM information. Inherently, this provision of information plays an important role in increasing the efficacy of related policies, as it enables citizens to improve their level of informedness, which ultimately affects their attitudes and behaviors. Such improvements in information provision appear to affect the level of citizens' responses to PM; for example, Zhou et al. [24] showed that opinions on travel plans were influenced by air quality classification, as have other similar studies related to air pollution and citizens' behaviors.

Not only academics and experts but also citizens are paying great attention to the dangers of PM. As previously discussed, a large number of studies have been conducted

to increase the accuracy of information provided. However, there is a lack of studies concerning how such increasing information affects citizens' behavior, as well as on the effect of implementing PM warning systems. Therefore, in this study, we explored the relationship between the concentration of PM and the visitation of major urban parks over the past decade in Seoul, South Korea. With this study, we also examined changes in behavior relating to outdoor activities and in decision making due to the PM forecasting and warning system.

3. Materials and Methods

3.1. Study Setting

3.1.1. PM Forecasting and Warning System in South Korea

In South Korea, a national-level forecasting and warning system that notifies the public of PM concentrations has been in operation since 2014. First introduced in Seoul in 2005, this system was passively implemented with different standards for each local government prior to its expansion. Since the mid-2010s, when PM issues began to significantly gain attention in South Korea, the system has been strengthened into an effective federal system on a unified basis.

PM concentrations are classified into four grades: good, normal, bad, and very bad (Table 1). During normal days, sensitive groups (e.g., children, the elderly, and those with correlated respiratory diseases) are recommended to avoid outdoor activities, whereas during bad or very bad periods, the public and sensitive groups are recommended to restrict excessive outdoor activities.

Table 1. Classification of particulate matter concentrations.

		(µg·m ³ , day)			
		Good	Normal	Bad	Very Bad
PM concentration	PM ₁₀	0–30	31–80	81–150	151<
	PM _{2.5}	0–15	16–35	36–75	76<

A PM₁₀ advisory is issued when the average concentration in an area is >150 µg m³ for ≥2 h, considering weather conditions, whereas a PM₁₀ warning is issued when the average concentration exceeds 300 µg m³ for 2 h. Alternatively, advisories and warnings for PM_{2.5} are issued when the average concentrations are 75 and 150 µg m³, respectively, for ≥2 h.

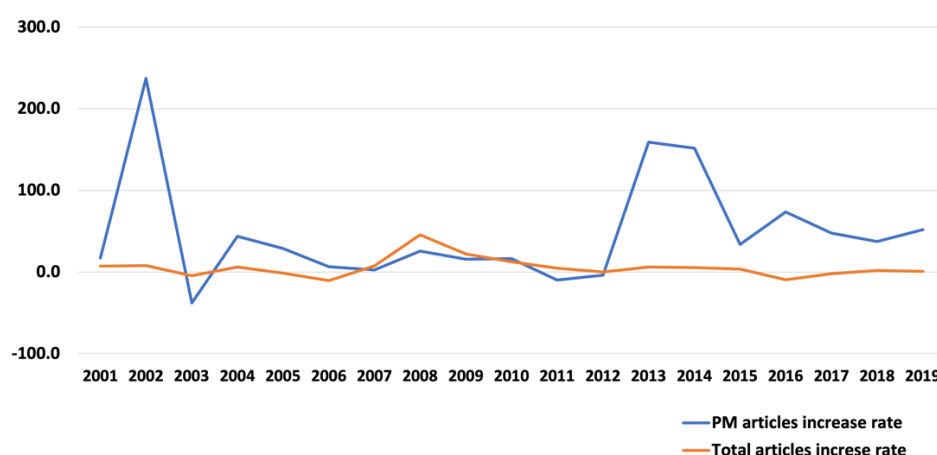
The government also provides appropriate guidelines for public action, along with PM forecasts and warnings, including restrictions on outdoor activities for sensitive groups; wearing masks when outside; refraining from visiting areas with high traffic; restrictions on the operation of outdoor sports facilities; and refraining from outdoor activities, such as park use.

3.1.2. Social Issues and Changes in PM Concentrations in South Korea

PM-related online news articles from the past 20 years were investigated in order to identify trends in public interest within South Korea. The BIGkinds, a big data analysis system for news articles provided by the Korea Press Foundation, was implemented for the analysis. The increasing number of online news articles generated annually is shown in Table 2. In particular, articles related to PM issues sharply increased compared to the total number of articles (Figure 1). It was revealed that the number of correlated news reports on PM has increased rapidly since the mid-2010s, with an article frequency of ~200 year^{−1} in the early 2000s, increasing by >300 times to ~64,000 year^{−1} by 2019. This phenomenon indicates that the issue of atmospheric PM has evolved beyond a simple environmental problem into the realm of social concern [25].

Table 2. Annual online news articles produced (data: BIGKinds).

Year	Number of PM Articles	Total Number of Articles	Year	Number of PM Articles	Total Number of Articles
2000	192	1,621,602	2010	1598 (+16.4%)	3,560,302 (+12.2%)
2001	225 (+17.2%)	1,737,440 (+7.1%)	2011	1438 (−10.0%)	3,728,829 (+4.7%)
2002	758 (+236.9%)	1,871,305 (+7.7%)	2012	1381 (−4.0%)	3,726,986 (+0.0%)
2003	470 (−38.0%)	1,788,110 (−4.4%)	2013	3577 (+159.0%)	3,952,681 (+6.1%)
2004	675 (+43.6%)	1,896,248 (+6.0%)	2014	9001 (+151.6%)	4,162,294 (+5.3%)
2005	870 (+28.9%)	1,866,553 (−1.6%)	2015	12,020 (+33.5%)	4,309,773 (+3.5%)
2006	924 (+6.2%)	1,665,812 (−10.8%)	2016	20,853 (+73.5%)	3,899,939 (−9.5%)
2007	946 (+2.4%)	1,788,570 (+7.4%)	2017	30,779 (+47.6%)	3,822,936 (−2.0%)
2008	1188 (+25.6%)	2,603,433 (+45.6%)	2018	42,219 (+37.2%)	3,893,067 (+1.8%)
2009	1373 (+15.6%)	3,171,855 (+21.8%)	2019	64,049 (+51.7%)	3,927,089 (+0.9%)

**Figure 1.** Comparison between PM-related and total article increases.

In addition, the number of articles that included the keywords “particulate matter” and “forecasting” revealed that the introduction of the PM forecasting and warning system reinforced public and social concerns regarding PM (Figure 2). The graph shows that the number of articles increased in January and May, decreased in September, and increased again as January approached. This seems to reflect the seasonal characteristics of PM in South Korea. According to the Seoul Metropolitan Government, a trend of high PM concentrations occurs in the period between winter and early spring due to seasonal factors, and domestic and foreign influences. Whereas the number of articles was relatively low when the PM forecasting and warning systems were handled by local governments, since the nationwide PM forecasting system was implemented in 2014, this number has increased. Thus, although concerns about PM stimulated the expansion of the PM forecasting and warning system, system implementation further motivated social discussion, as indicated by the growth in related articles. Furthermore, the fact that concern regarding PM concentrations has largely developed in conjunction with the introduction of the PM forecasting and warning system is a testament to the system’s impact on the public, as the level of public information regarding PM significantly shifted between 2014 and 2015, thereby potentially changing citizens’ perceptions and attitudes.

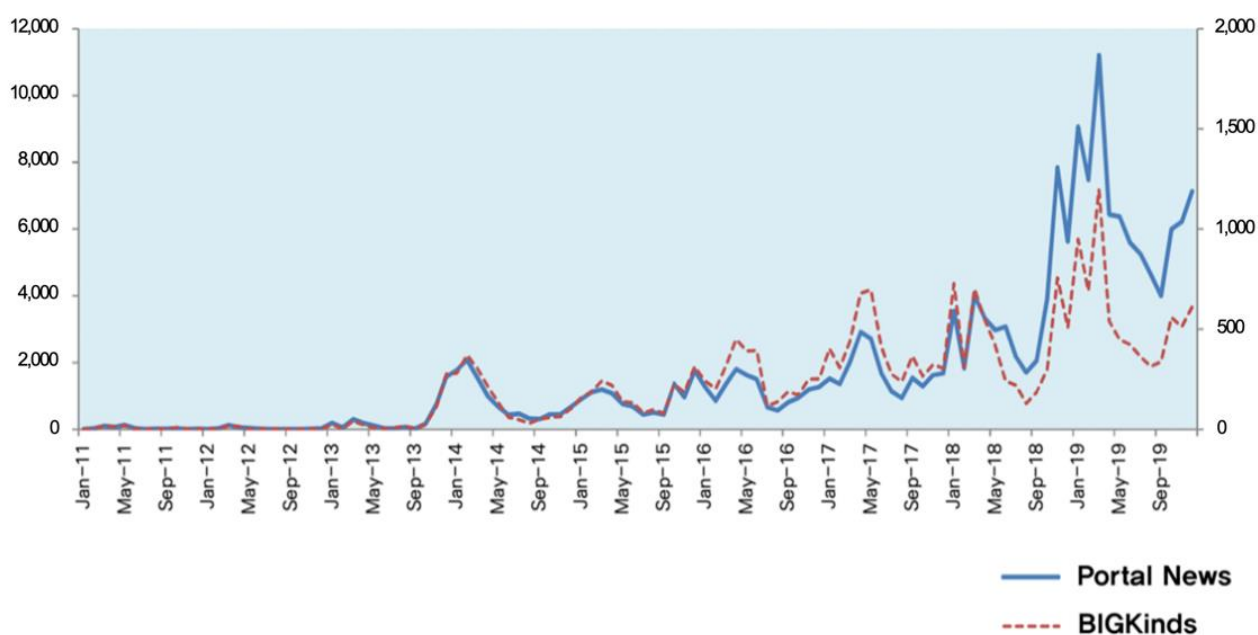


Figure 2. Frequency of media reporting “particulate matter forecasting” as a keyword (in Korean).

Notably, it was found that the average annual PM concentrations in South Korea have gradually decreased since 2002, when the PM_{10} concentration was $61 \mu g m^{-3}$, on average, and have remained $<50 \mu g m^{-3}$ since 2012 (Table 3).

Table 3. Average concentration of PM_{10} in the past 20-year period ($\mu g \cdot m^{-3}$; Korea Environment Corporation).

Year	Concentration	Year	Concentration
2000	53	2010	51
2001	58	2011	50
2002	61	2012	45
2003	58	2013	49
2004	59	2014	49
2005	57	2015	48
2006	59	2016	47
2007	58	2017	45
2008	54	2018	41
2009	53	2019	41

Although PM pollution is treated as a serious social issue, it is difficult to judge whether air quality, especially PM concentrations, has deteriorated over time when comparing various measurement results [26]. Although average annual PM_{10} concentrations have generally decreased since 2000, public concern regarding PM has increased sharply since 2013 (Figure 3).

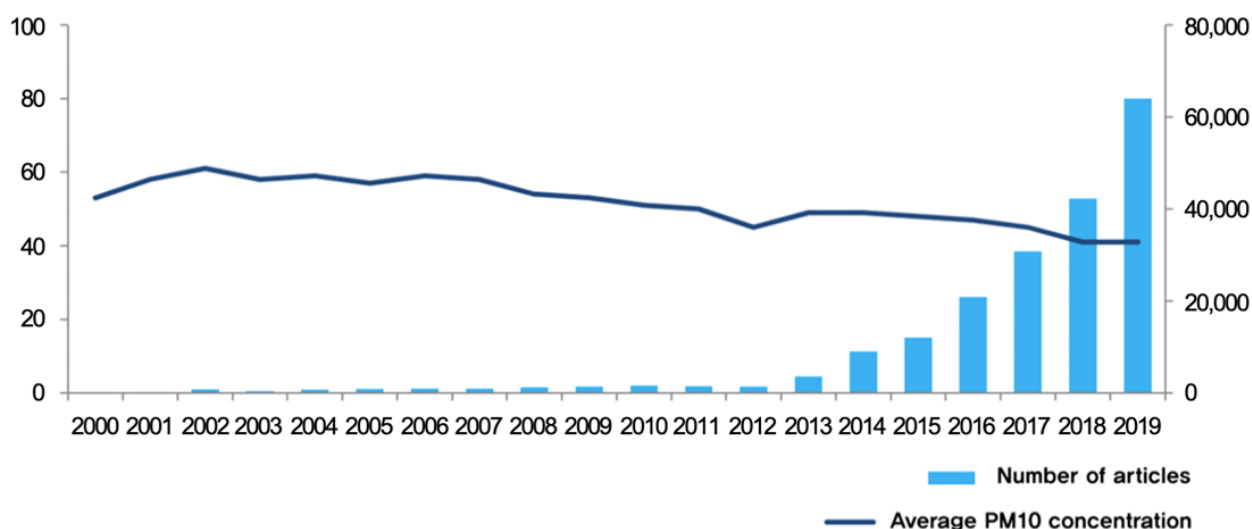


Figure 3. Average annual PM₁₀ concentration levels compared to the number of online articles over the 20-year period from 2000 to 2019.

Despite the decreasing PM concentration, the major social concern regarding PM pollution is related to the negative effects of PM on human health and the environment. In particular, the IARC (International Agency for Research on Cancer) classified PM as a carcinogenic agent for humans (Group 1), and the government announced the implementation of the PM forecasting system and set the PM_{2.5} concentration standard. Consequently, public concern and the number of articles on PM have increased [25]. This phenomenon may also be due to the increased expectations of the public regarding air quality management. Additionally, PM concentrations are still higher than those in other OECD countries [27], possibly contributing to the public concern [25]. Furthermore, whereas the average annual concentration of PM has decreased over time, the frequency of high-concentration cases has increased, as indicated by the steep increase in peak concentration levels within a given year since 2015, with the number of days with high PM concentrations increasing from 5 d in 2015 to 16 d in 2019. Accordingly, the media have increased their coverage of PM, likely impacting the level of public concern [28].

This phenomenon has been interpreted in conjunction with the agenda-setting theory, whereby media (e.g., newspapers, news, and current affairs) contribute to the public's agenda setting, and the agenda-setting function refers to instances where a topic reported in mass media is accepted as being important by the public [29,30].

According to priming theory, notably developed from the agenda-setting theory, if the media frequently or weightily report a particular issue, the public uses that issue as a basis for judgment during evaluation. Therefore, mass media influence what the public should think about, as well as how they think about it [29]. Thus, it appears likely that the agenda-setting and priming effects increased the public's PM-related concerns. Furthermore, the issue of high PM concentrations reported through mass media is disseminated and reproduced through online media, such as SNS (social networking service) and blogs, affecting the perception of citizens, as well as overall socioeconomic activities.

Accordingly, in the present study, we aimed to examine whether PM concentrations in South Korea affected citizens' use of urban parks. Furthermore, we also aimed to determine whether the PM forecasting and warning system has a meaningful effect on decision making as a case study. To this end, three urban park sites were selected, including indoor and outdoor spaces in Seoul: Gyeongbokgung Palace, Deoksugung Palace, and the National Museum of Korea.

3.2. Data Collection and Analysis

3.2.1. Data

PM concentration data used in this study were collected by city air monitoring stations across 25 boroughs in Seoul for 9 years (2011–2019). Notably, only data up to 2019 were used to exclude data following the outbreak of COVID-19. Currently, air quality in South Korea is measured via 11 types of monitoring stations: city, roadside, and suburban air quality monitoring stations; acid deposition, background density, heavy metal, harmful material, photochemical pollutant, global atmosphere, and PM_{2.5} monitoring stations; and air pollution concentration stations. All monitoring stations measure SO₂, CO, O₃, NO₂, PM₁₀, PM_{2.5}, etc. Notably, the average PM concentration in Seoul was equivalent to the average value measured by the city air monitoring stations.

Data were collected from Air Korea, a public website operated by the Korea Environment Corporation, with the final released PM concentration data from this site being used. In addition to PM concentrations, five additional variables were selected, namely PM warning issuance; three weather variables, i.e., temperature, precipitation, and wind speed; and holiday conditions. The number of visitors to the case study sites was evaluated from 1 January 2011 to 31 December 2019 (total of nine years), and all visitor data were obtained upon request from the agency in charge of each site.

3.2.2. Analysis Method

Multiple regression analysis was conducted separately for each of the three target sites, as the impact of the PM concentration on users was analyzed by examining the differences between the results for different sites. In addition, we analyzed the effect of PM information on users according to whether an advisory or warning was issued. As stated above, because the PM forecasting and warning system expanded after 2014, system efficacy was expected to show an inflection point near 2015. Additionally, it was confirmed that articles related to PM information have rapidly increased since 2018. Considering the time required for system establishment, it was necessary to examine this period separately. Therefore, the following three periods were recognized in the present study: an introduction period of PM issues and forecasting–warning systems, 2011–2015; the spread period of PM issues and the system, 2016–2017; and the established period of PM issues, 2018–2019. Multiple regression analysis was then conducted for each period. The software used for the analysis was R-Studio.

3.2.3. Case Study Sites

To analyze the impact of PM pollution issues on urban park visitors, three case study sites located in Seoul were selected: Gyeongbokgung Palace (Site 1), Deoksugung Palace (Site 2), and the National Museum of Korea (Site 3). These sites are representative of places in Seoul visited by >2–3 million Korean nationals each year. Notably, Sites 1 and 2 have historically only been available to specific social classes; however, presently, they are places that provide historical and cultural experiences to all and play important roles as parks and open spaces. These case study sites are less affected by seasonal factors compared to other types of urban parks, as there is substantial cultural and commercial attraction for visitors, resulting in a relatively stable number of visitors. In addition, the Cultural Heritage Administration systematically manages the number of tourists per day to oversee data quality. Moreover, Sites 1 and 2 are typical parks mostly confined to outdoor spaces, whereas the main spaces of Site 3 are indoors. Therefore, differences were expected in PM pollution effects, depending on whether the case study site was inside or outside.

4. Results

4.1. Analysis on PM Concentrations and Visitors

From 2011 to 2019, PM concentrations gradually decreased at the study sites (Figure 4). The daily PM₁₀ concentration data showed that average concentrations decreased over the entire period, with this tendency being clearly observed in the monthly average PM

concentration data, which presented a slight increase from 2012 to 2016 before decreasing over the following years.

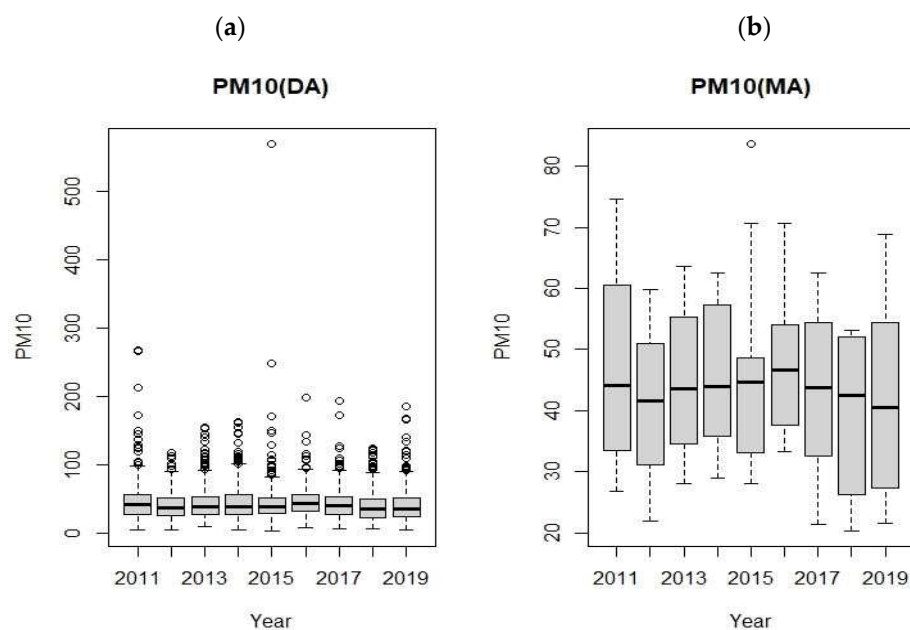


Figure 4. PM₁₀ concentration changes in Seoul (2011–2019). (a) Daily average (DA) analysis of PM₁₀ concentration; (b) monthly average (MA) analysis of PM₁₀ concentration (each box plot with whiskers represents the data variation of PM concentration for each year).

According to the air quality report released every month by the Seoul Metropolitan Government, PM advisories were issued 38 times on 61 days from 2007 to 2019 (Table 4). In addition, a PM warning was issued once (for one day). Although the number of PM warnings was not high, considering that as the system is implemented, the media emphasize PM risks while mentioning warning issuances, it is likely that PM risks will be reflected more in public behavior over time.

Table 4. PM advisory and warning issuance in Seoul, South Korea, 2007–2010 and 2013–2019.

Year	PM Advisory		PM Warning	
	Frequency of Issuance	Number of Days of Issuance	Frequency of Issuance	Number of Days of Issuance
2007	2	4	0	0
2008	2	3	0	0
2009	2	4	0	0
2010	1	3	0	0
2011	0	0	0	0
2012	0	0	0	0
2013	1	2	0	0
2014	2	4	0	0
2015	3	5	0	0
2016	6	7	0	0
2017	6	10	0	0
2018	5	5	1	1
2019	8	14	0	0
Total	38	61	1	1

The annual average number of Korean visitors to each case study site over the nine years analyzed was: Site 1, 3,257,590; Site 2, 1,259,939; and Site 3, 3,042,230 (Table 5).

Although the number of visitors decreased during some periods, the number of overall visitors increased at all three sites since 2011.

Table 5. Total annual number of Korean visitors at each site.

Year	Site 1	Site 2	Site 3
2011	2,515,057	1,036,662	2,910,381
2012	3,098,350 (+23.2%)	816,707 (−21.2%)	2,626,093 (−9.8%)
2013	2,941,157 (−5.1%)	1,035,879 (+26.8%)	2,808,088 (+6.9%)
2014	3,657,760 (+24.4%)	1,151,792 (+11.2%)	3,408,851 (+21.4%)
2015	3,347,046 (−8.5%)	1,088,531 (−5.5%)	2,656,691 (−22.1%)
2016	3,122,183 (−6.7%)	1,271,654 (+16.8%)	3,212,143 (+20.9%)
2017	3,336,671 (+6.9%)	1,522,049 (+19.7%)	3,363,889 (+4.7%)
2018	3,425,247 (+2.7%)	1,371,381 (−9.9%)	3,178,236 (−5.5%)
2019	3,874,837 (+13.1%)	2,044,800 (+49.1%)	3,215,697 (+1.2%)

The change in the number of visitors by PM concentration showed that the higher the PM concentration, the lower the number of visitors; however, the behavioral change was not remarkably significant for Site 1 (Figure 4, blue line). When the PM advisories and warnings were issued, it was confirmed that there was a slight decrease in the number of visitors, although it was difficult to determine whether this presented a clear trend (Figure 5, red line).

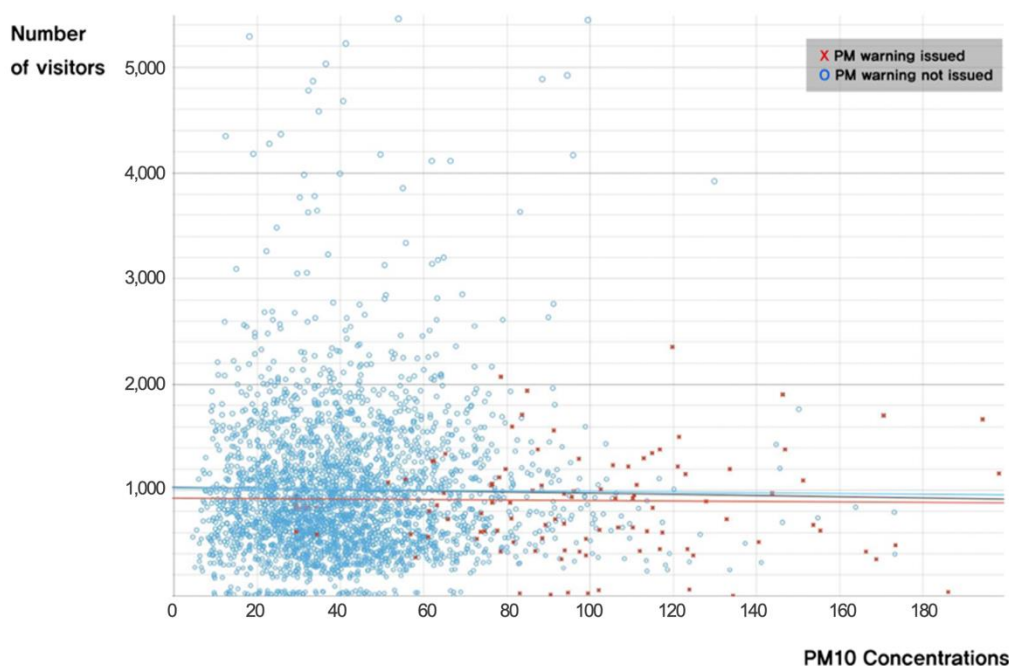


Figure 5. Scatter plot of PM concentration levels and the number of daily visitors (Site 1). Blue line: changes in the number of visitors based on PM concentration; red line: changes in the number of visitors based on PM advisories and warnings.

The results for Site 2 also indicated that the number of visitors slightly decreased when PM concentrations increased and PM advisories and warnings were issued (Figure 6).

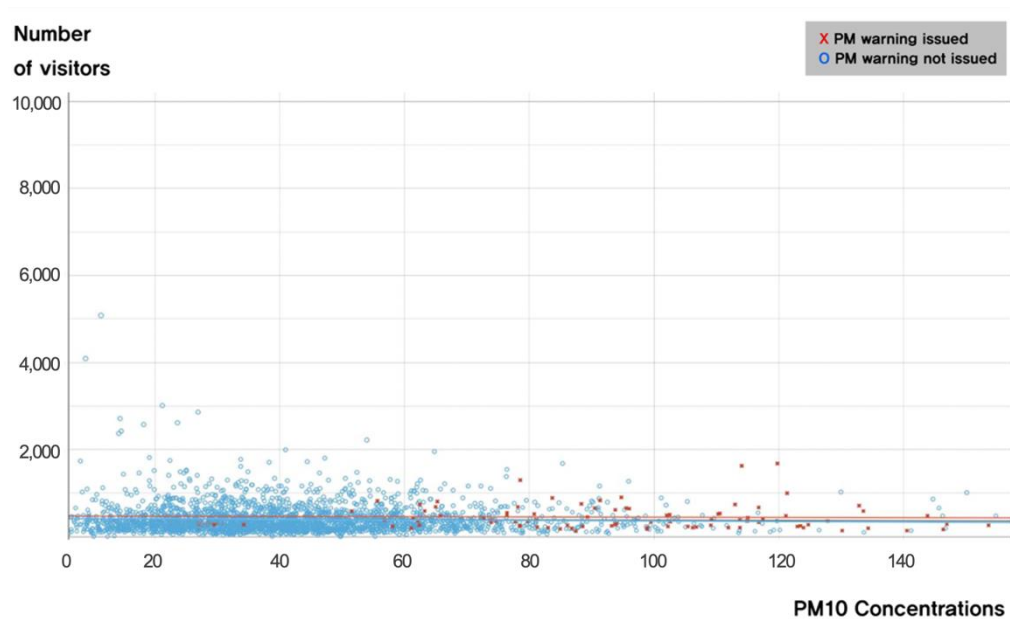


Figure 6. Scatter plot of PM concentration levels and the number of daily visitors—Site 2.

Alternatively, in the case of Site 3, the number of visitors decreased as the PM concentration increased and PM advisory and warning were issued (Figure 7).

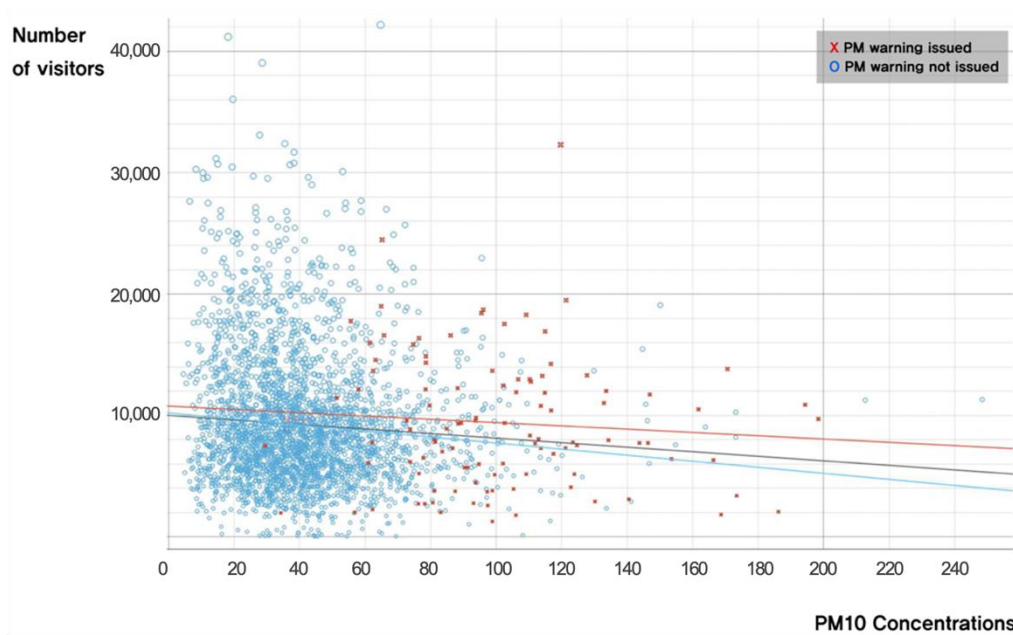


Figure 7. Scatter plot of PM concentration levels and the number of daily visitors (Site 3).

Over the past 9 years, PM concentrations have decreased overall, whereas the number of visitors to each site has increased. In addition, the number of visitors slightly decreased when PM concentrations were high; however, it is difficult to conclude a direct causality between the two or even significant changes in visitors' behavior. Besides the PM concentrations, various variables affect user behavior, which must be considered comprehensively.

4.2. Multiple Regression Analyses by Site

At Site 1, the result of regression was $F = 94.878$, $p < 0.001$, with an R^2 of 0.186 (adjusted $R^2 = 0.184$). The results showed that both weather and holiday variables affected the number

of visitors (Table 6). The number of visitors increased when temperatures and sunshine duration were higher, as well as when precipitation and wind speeds were lower. Holidays also led to significantly increased numbers of visitors; however, PM concentrations and warning issuance variables were not statistically significant.

Table 6. Multiple regression results (Site 1) (2011–2019).

	Unstandardized Coefficient		Standardized Coefficient β	t	p	Collinearity Statistic	
	B	Std. Error				Tolerance	VIF
constants	4713.666	655.171		7.195	0.000		
Temperature	175.689	14.185	0.218	12.386	0.000	0.907	1.103
Precipitation	−56.493	11.972	−0.087	−4.719	0.000	0.824	1.213
Wind speed	−381.884	172.794	−0.038	−2.210	0.027	0.956	1.046
Sunshine duration	253.205	39.454	0.115	6.418	0.000	0.872	1.147
Holiday	6083.789	305.782	0.333	19.896	0.000	0.999	1.001
PM ₁₀	5.645	6.283	0.017	0.899	0.369	0.750	1.333
Warning issuance	−781.918	905.027	−0.016	−0.864	0.388	0.800	1.250

$R^2 = 0.186$, adjusted $R^2 = 0.184$, $F = 94.878$ ($p < 0.001$).

At Site 2, the result of regression was $F = 69.303$, $p < 0.001$, with an R^2 of 0.146 (adjusted $R^2 = 0.144$). It was found that temperature, precipitation, wind speed, sunshine, and holiday variables all had a significant impact on the number of visitors (Table 7). In contrast with the results for Site 1, PM concentration and warning issuance were slightly statistically significant relative to the number of visitors, as the results showed that the higher the PM₁₀ concentrations, the fewer the visitors; however, contrary to expectations, the number of visitors increased when a warning was issued.

Table 7. Multiple regression results (Site 2) (2011–2019).

	Unstandardized Coefficient		Standardized Coefficient β	t	p	Collinearity Statistic	
	B	Std. Error				Tolerance	VIF
constants	3625.448	346.387		10.466	0.000		
Temperature	37.591	7.279	0.094	5.164	0.000	0.905	1.105
Precipitation	−21.401	6.026	−0.068	−3.551	0.000	0.831	1.203
Wind speed	−659.079	89.133	−0.131	−7.394	0.000	0.956	1.046
Sunshine duration	107.420	20.320	0.098	5.286	0.000	0.877	1.141
Holiday	2768.510	156.489	0.307	17.691	0.000	0.998	1.002
PM ₁₀	−5.928	3.479	−0.034	−1.704	0.089	0.764	1.309
Warning issuance	778.104	468.484	0.032	1.661	0.097	0.820	1.220

$R^2 = 0.146$, adjusted $R^2 = 0.144$, $F = 69.303$ ($p < 0.001$).

At Site 3, the result of regression was $F = 201.407$, $p < 0.001$, with an R^2 of 0.323 (adjusted $R^2 = 0.321$). The number of visitors increased when temperatures were high, when precipitation and sunshine were low, and during holidays (Table 8); wind speed was not statistically significant. It was also observed that higher PM₁₀ concentrations decreased the number of visitors, and similarly to Site 2, the issuance of PM warnings increased the number of visitors.

Table 8. Multiple regression results (Site 3) (2011–2019).

	Unstandardized Coefficient		Standardized Coefficient	t	p	Collinearity Statistic	
	B	Std. Error	β			Tolerance	VIF
constants	7588.363	367.598		20.643	0.000		
Temperature	69.409	7.824	0.141	8.871	0.000	0.901	1.110
Precipitation	−11.704	6.365	−0.031	−1.839	0.066	0.828	1.207
Wind speed	−77.187	95.491	−0.013	−0.808	0.419	0.955	1.047
Sunshine duration	−75.489	21.681	−0.056	−3.482	0.001	0.874	1.144
Holiday	6008.352	169.331	0.537	35.483	0.000	0.999	1.001
PM ₁₀	−15.920	3.731	−0.075	−4.267	0.000	0.744	1.344
Warning occurrence	1303.524	491.846	0.045	2.650	0.008	0.800	1.250

$R^2 = 0.323$, adjusted $R^2 = 0.321$, $F = 201.407$ ($p = 0.001$).

4.3. Multiple Regression Analysis by Period

The results for Site 1 across each period are listed in Table 9. The table represents the regression coefficient, β represents each variable's influence, and $t(P)$ represents the significance. During period 1, temperature, precipitation, sunshine, and holidays all significantly affected the number of visitors. PM concentrations were also found to increase the number of visitors, although this effect was only slightly statistically significant. During period 2, temperature, precipitation, and holidays affected visitor numbers, whereas PM concentrations and warning issuance did not show any such effects. The results of period 3 showed that temperature, precipitation, sunshine, and holidays affected the number of visitors, whereas PM₁₀ concentrations were not significant. It was thus confirmed that PM warning issuance partially decreased the number of visitors during this period.

Table 9. Multiple regression result (Site 1).

	B	SE	β	t (P)	VIF
Period 1 (2011–2015)	Constants	3753.558	810.561	4.631 (0.000)	
	Temperature	196.353	16.793	0.271	11.693 (0.000)
	Precipitation	−44.240	13.041	−0.083	−3.392 (0.001)
	Wind speed	−338.493	202.028	−0.038	−1.675 (0.094)
	Sunshine duration	336.122	47.074	0.169	7.140 (0.000)
	Holiday	5375.496	364.648	0.328	14.742 (0.000)
	PM ₁₀	11.287	6.658	0.042	1.695 (0.090)
	Warning issuance	224.673	1480.253	0.004	0.152 (0.879)
$R^2 = 0.224$, adjusted $R^2 = 0.221$, $F = 64.762$ ($p = 0.001$)					
Period 2 (2016–2017)	Constants	7547.727	2032.690	3.713 (0.000)	
	Temperature	192.504	37.789	0.200	5.094 (0.000)
	Precipitation	−82.371	32.470	−0.104	−2.537 (0.011)
	Wind speed	−721.298	602.206	−0.047	−1.198 (0.231)
	Sunshine duration	116.399	104.893	0.045	1.110 (0.268)
	Holiday	6273.455	813.489	0.290	7.712 (0.000)
	PM ₁₀	−28.467	21.102	−0.063	−1.349 (0.178)
	Warning issuance	1899.820	2776.437	0.031	0.684 (0.494)

Table 9. Cont.

		B	SE	β	t (P)	VIF
$R^2 = 0.142$, adjusted $R^2 = 0.133$, $F = 14.682$ ($p = 0.001$)						
Period 3 (2018–2019)	Constants	4782.207	1564.201		3.057 (0.002)	
	Temperature	116.989	31.085	0.141	3.764 (0.000)	1.231
	Precipitation	−70.985	33.125	−0.083	−2.143 (0.032)	1.318
	Wind speed	−23.461	524.439	−0.002	−0.045 (0.964)	1.104
	Sunshine duration	206.647	86.063	0.092	2.401 (0.017)	1.276
	Holiday	7499.755	644.139	0.396	11.643 (0.000)	1.013
	PM ₁₀	11.069	17.519	0.030	0.632 (0.528)	2.003
	Warning issuance	−2625.457	1503.922	−0.078	−1.746 (0.081)	1.762
	$R^2 = 0.205$, adjusted $R^2 = 0.197$, $F = 25.647$ ($p = 0.001$)					

According to the results for period 1 at Site 2, temperature, precipitation, wind speed, sunshine, and holidays all affected the number of visitors; furthermore, the number of visitors also increased with PM concentration (Table 10). The results for period 2 showed that temperature, precipitation, and holidays affected the number of visitors, whereas PM concentrations were negatively correlated with the number of visitors. During period 3, holiday and weather variables (excluding wind speed) significantly increased the number of visitors; however, the PM concentrations and warning issuance were not statistically significant.

Table 10. Multiple regression result (Site 2).

		B	SE	β	t (P)	VIF
Period 1 (2011–2015)	Constants	2211.288	220.560		10.026 (0.000)	
	Temperature	28.137	4.479	0.135	6.282 (0.000)	1.098
	Precipitation	−13.114	3.291	−0.089	−3.984 (0.000)	1.190
	Wind speed	−324.371	53.570	−0.127	−6.055 (0.000)	1.048
	Sunshine duration	77.829	12.391	0.137	6.281 (0.000)	1.128
	Holiday	2371.709	96.531	0.506	24.569 (0.000)	1.003
	PM ₁₀	4.992	1.961	0.058	2.545 (0.011)	1.209
	Warning issuance	−53.500	385.501	−0.003	−0.139 (0.890)	1.116
	$R^2 = 0.336$, adjusted $R^2 = 0.333$, $F = 113.763$ ($p = 0.001$)					
Period 2 (2016–2017)	Constants	4223.595	1478.308		2.857 (0.004)	
	Temperature	87.986	26.902	0.131	3.271 (0.001)	1.098
	Precipitation	−54.630	25.316	−0.091	−2.158 (0.031)	1.228
	Wind speed	−502.642	437.781	−0.046	−1.148 (0.251)	1.095
	Sunshine duration	64.665	78.234	0.034	0.827 (0.409)	1.175
	Holiday	3697.079	590.782	0.242	6.258 (0.000)	1.027
	PM ₁₀	−35.862	15.551	−0.107	−2.306 (0.021)	1.492
	Warning issuance	2031.193	2022.684	0.046	1.004 (0.316)	1.418

Table 10. Cont.

		B	SE	β	t (P)	VIF
$R^2 = 0.094$, adjusted $R^2 = 0.084$, $F = 9.243$ ($p = 0.001$)						
Period 3 (2018–2019)	Constants	2959.577	688.657		4.298 (0.000)	
	Temperature	27.791	13.564	0.081	2.049 (0.041)	1.223
	Precipitation	−32.718	14.883	−0.089	−2.198 (0.028)	1.288
	Wind speed	−43.228	229.515	−0.007	−0.188 (0.851)	1.109
	Sunshine duration	142.983	37.905	0.152	3.772 (0.000)	1.260
	Holiday	2954.598	277.816	0.384	10.635 (0.000)	1.015
	PM ₁₀	3.614	7.700	0.023	0.469 (0.639)	1.895
	Warning issuance	−300.427	645.596	−0.022	−0.465 (0.642)	1.684
$R^2 = 0.200$, Adjusted $R^2 = 0.191$, $F = 22.238$ ($p = 0.001$)						

At Site 3, temperature, precipitation, and holidays increased the number of visitors during period 1 (Table 11). Furthermore, PM concentrations and warning issuance significantly affected visitor numbers (PM concentrations were negatively correlated, whereas warning issuances were positively correlated). The results for period 2 showed that the PM concentrations significantly decreased the number of visitors; however, it was found that PM warning issuances did not affect visitor numbers. During period 3, temperature, wind speed, and holidays affected the number of visitors, whereas high PM concentrations were negatively correlated with the number of visitors. Moreover, as with the analysis results of period 1, the number of visitors actually increased with the issuance of PM warnings.

Table 11. Multiple regression result (Site 3).

		B	SE	β	t (P)	VIF
Period 1 (2011–2015)	Constants	7678.537	534.792		14.358 (0.000)	
	Temperature	99.039	10.865	0.204	9.115 (0.000)	1.101
	Precipitation	−14.075	7.840	−0.042	−1.795 (0.073)	1.189
	Wind speed	−146.874	129.210	−0.025	−1.137 (0.256)	1.050
	Sunshine duration	−108.344	29.883	−0.082	−3.626 (0.000)	1.129
	Holiday	5379.336	232.794	0.494	23.108 (0.000)	1.003
	PM ₁₀	−9.917	4.704	−0.050	−2.108 (0.035)	1.212
	Warning issuance	2046.623	917.616	0.050	2.230 (0.026)	1.118
$R^2 = 0.302$, adjusted $R^2 = 0.299$, $F = 94.696$ ($p = 0.001$)						
Period 2 (2016–2017)	Constants	9485.285	834.043		11.373 (0.000)	
	Temperature	−23.133	15.443	−0.047	−1.498 (0.135)	1.116
	Precipitation	−7.181	13.478	−0.017	−0.533 (0.594)	1.227
	Wind speed	−129.007	247.430	−0.016	−0.521 (0.602)	1.105
	Sunshine duration	−67.234	43.962	−0.049	−1.529 (0.127)	1.170
	Holiday	6992.099	343.490	0.608	20.356 (0.000)	1.018
	PM ₁₀	−33.640	8.819	−0.140	−3.814 (0.000)	1.537
	Warning issuance	1165.574	1140.712	0.036	1.022 (0.307)	1.453

Table 11. Cont.

	B	SE	β	t (P)	VIF
$R^2 = 0.386$, adjusted $R^2 = 0.380$, $F = 63.056$ ($p = 0.001$)					
Constants	7352.828	822.664		8.938 (0.000)	
Period 3 (2018–2019)					
Temperatures	84.479	16.393	0.169	5.153 (0.000)	1.228
Precipitation	−11.264	17.670	−0.022	−0.637 (0.524)	1.312
Wind speed	−519.714	273.991	−0.059	−1.897 (0.058)	1.113
Sunshine duration	32.538	45.428	0.024	0.716 (0.474)	1.270
Holiday	6429.616	344.812	0.557	18.647 (0.000)	1.013
PM ₁₀	−27.379	9.145	−0.125	−2.994 (0.003)	1.969
Warning issuance	2122.759	784.989	0.106	2.704 (0.007)	1.737
$R^2 = 0.373$, adjusted $R^2 = 0.367$, $F = 60.544$ ($p = 0.001$)					

5. Discussion

The results across the entire analysis period showed that weather and holidays consistently affected the number of visitors to the case study sites. At Sites 2 and 3, PM concentrations were found to have a negative effect on citizens' outdoor activities; however, contrary to expectations, the results showed that the number of users increased when PM warnings were issued here (significant at the $\alpha = 0.1$ level). This may have been due to the fact that PM advisories and warnings were issued when the PM concentration levels exceeded the standard levels, and therefore, the total number of issuances was insufficient to obtain an adequate sample size.

The results of each period did not confirm that a greater degree of PM information dissemination led to fewer visits by citizens to the case study sites; however, the results for period 3 indicated that PM warning issuances impacted the number of visitors at Site 1, thus supporting the effects of public information efforts. These results can also be considered in conjunction with the effects of PM discussed by the media. According to Cha et al. [31], agenda setting by the media in South Korea varied in each period (particularly between 2018 and 2019), with reports on the impact of PM on human health decreasing, and on the government's policies increasing, in addition to conflicts between the government and the public.

However, Site 3, notably a mostly indoor space, received more visitors when PM warnings were issued. Considering the results for Site 1, this result may indicate that awareness of the risks of PM caused citizens to move from outdoor to indoor spaces. These findings are notably similar to those reported by Choi et al. [32], which indicated that people tend to gather in indoor spaces during periods of high PM concentrations.

There are limitations in interpreting the results of this study, as citizens' decisions to use urban parks are affected by various variables, including changes in socioeconomic status, citizens' thoughts and preferences on leisure, and individual interest levels in urban parks; however, as confirmed by the results of this study, the influence of atmospheric environmental conditions, such as weather and PM concentrations, can affect whether people visit an urban park, which implies the possibility that PM pollution is a serious social issue.

As indicated in the literature review [4,12,18], the level of PM concentration affects people's willingness to participate in outdoor activities; this was also derived from the results of Site 2 and 3 in this research. However, the effectiveness of PM forecasting and warning systems has not been explored enough so far. The research result of the Site 3 case study indicated that PM forecasting and warning systems affect people's willingness and actual behaviors towards outdoor activities. In terms of prediction and warning accuracies, current research has been mainly focused on technical aspects based on algorithms; how-

ever, in this study, we validated the effectiveness of prediction and warning systems based on actual evidence, including urban park visitors.

Perceptual recognition affects human behavior. According to Lee et al. [33], citizens' perception of PM affects decision making more than the PM concentration data. In order to enhance people's cognitive response to PM, together with PM forecasting and warning, systematic and constant feeding information and management strategies around PM could minimize PM's negative impacts that have already occurred in peoples' daily lives. As part of this, the PM forecasting and warning system was introduced in South Korea. The effectiveness of the warning system can be improved by securing continuous and detailed quality data. The case studies presented in this research are based on Seoul's highly regarded tourist attractions; therefore, the study results cannot be generalized to represent people's everyday life. In addition, the current system was implemented at a time when PM levels were already serious, predicting up to two days. Therefore, future research needs to consider whether such systems affect decision making in daily life, as well as various types of urban parks and circulation data.

6. Conclusions

In this study, the effects of PM pollution and PM forecasting and warning systems in South Korea were analyzed. Whereas research to date has focused on improving prediction and accuracy, in this study, we explored the effectiveness of the PM forecasting and warning system with respect to citizens' behavior.

Three case study park sites in South Korea was analyzed. The number of visitors to each site was, in part, explained by weather and holiday variables; however, it was also confirmed that PM concentrations negatively impacted citizens' outdoor activities, as indicated by fewer visitors at Sites 2 and 3 when PM concentrations were high. An examination across the entire study period suggested that the PM forecasting and warning system influenced park use behaviors; however, contrary to expectations, warning issuance was not statistically significantly correlated with visitors or even correlated with an increase in visitors. Additionally, when comparing the adjusted R^2 of each model, it was found that the explanatory power of the model for Site 3 was higher than that of the models for Sites 1 and 2. Moreover, three distinct periods were identified and analyzed based on the amount of PM information being provided by the mass media to the public, as well as the functionality of the PM forecasting–warning system. Following the classification analyses for different periods, the hypothesis that the level of PM information distribution will significantly impact citizens' behavioral responses was not clearly confirmed; however, the results for period 3 at Site 1 showed that PM warning issuances significantly decreased the number of visitors, whereas for Site 3, where the primary park space is located indoors, the number of visitors increased when PM warnings were issued.

It has not been long since the PM forecasting and warning system was introduced nationwide in South Korea; therefore, it is not yet clear whether the system has proven to be efficient or produce empirical results. In this study, analyzed data accumulated until 2019 after the implementation of the PM forecasting and warning system; it was possible to estimate that the PM forecasting and warning system partially affects citizens' park use behavior. As continuous data are added in the future, the effectiveness of the system could be clearly assured. In addition, future studies are required that analyze changes in citizens' perception, different types of urban open spaces, and circulations data.

Author Contributions: Conceptualization, Y.S., S.K., and J.P.; writing—original draft preparation, Y.S. and S.K.; writing—review and editing, K.A.; supervision, K.A., S.-W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Acknowledgments: This paper was written as part of Konkuk University's research support program for its faculty on sabbatical leave in 2020. This paper was also supported by Korea Forest Service (Korea Forestry Promotion Institute) (FTIS 2021331A00-2223-AA01) and the National Research Foundation of Korea (NRF) grant funded by the Korea government (MSIT) (No. NRF-2021R1F1A1059444).

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

References

1. Tainio, M.; Jovanovic Andersen, Z.; Nieuwenhuijsen, M.J.; Hu, L.; de Nazelle, A.; An, R.; Garcia, L.M.T.; Goenka, S.; Zapata-Diomed, B.; Bull, F.; et al. Air Pollution, Physical Activity and Health: A Mapping Review of the Evidence. *Environ. Int.* **2021**, *147*, 105954. [\[CrossRef\]](#) [\[PubMed\]](#)
2. Roberts, J.D.; Voss, J.D.; Knight, B. The Association of Ambient Air Pollution and Physical Inactivity in the United States. *PLoS ONE* **2014**, *9*, e90143. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Xu, Y.; Liu, Y.; Chang, X.; Huang, W. How Does Air Pollution Affect Travel Behavior? A Big Data Field Study. *Transp. Res. Part D Transp. Environ.* **2021**, *99*, 103007. [\[CrossRef\]](#)
4. An, R.; Shen, J.; Ying, B.; Tainio, M.; Andersen, Z.J.; de Nazelle, A. Impact of Ambient Air Pollution on Physical Activity and Sedentary Behavior in China: A Systematic Review. *Environ. Res.* **2019**, *176*, 108545. [\[CrossRef\]](#)
5. Lu, J.G. Air Pollution: A Systematic Review of Its Psychological, Economic, and Social Effects. *Curr. Opin. Psychol.* **2020**, *32*, 52–65. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Wendel, J. Air Pollution Ranks as Largest Health Risk. *Eos Trans. AGU* **2014**, *95*, 120. [\[CrossRef\]](#)
7. Xu, Y.; Yang, W.; Wang, J. Air Quality Early-Warning System for Cities in China. *Atmos. Environ.* **2017**, *148*, 239–257. [\[CrossRef\]](#)
8. Wang, S.; Feng, X.; Zeng, X.; Ma, Y. A Study on Variation of Concentrations of Particulate Matter with Different Sizes in Lanzhou, China. *Atmos. Environ.* **2009**, *43*, 2823–2828. [\[CrossRef\]](#)
9. Khaniabadi, Y.O.; Goudarzi, G.; Daryanoosh, S.M.; Borgini, A.; Tittarelli, A.; De Marco, A. Exposure to PM10, NO2, and O3 and Impacts on Human Health. *Environ. Sci. Pollut. Res.* **2017**, *24*, 2781–2789. [\[CrossRef\]](#)
10. Masselot, P.; Chebana, F.; Lavigne, É.; Campagna, C.; Gosselin, P.; Ouarda, T.B.M.J. Toward an Improved Air Pollution Warning System in Quebec. *IJERPH* **2019**, *16*, 2095. [\[CrossRef\]](#)
11. Cascio, W.E. Wildland Fire Smoke and Human Health. *Sci. Total Environ.* **2018**, *624*, 586–595. [\[CrossRef\]](#)
12. Hong, H.J.; Park, Y.H.; Yu, H.S. *A Preliminary Study on Developing Environmental Assessment Methods in Urban Stream Watersheds*; Korea Environment Institute: Sejong, Korea, 2013.
13. Kim, K.-H.; Kabir, E.; Kabir, S. A Review on the Human Health Impact of Airborne Particulate Matter. *Environ. Int.* **2015**, *74*, 136–143. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Krewski, D. Evaluating the Effects of Ambient Air Pollution on Life Expectancy. *N. Engl. J. Med.* **2009**, *360*, 413–415. [\[CrossRef\]](#) [\[PubMed\]](#)
15. Jeong, S.J. The Impact of Air Pollution on Human Health in Suwon City. *Asian J. Atmos. Environ.* **2013**, *7*, 227–233. [\[CrossRef\]](#)
16. Hyslop, N.P. Impaired Visibility: The Air Pollution People See. *Atmos. Environ.* **2009**, *43*, 182–195. [\[CrossRef\]](#)
17. Xu, J.; Chi, C.S.F.; Zhu, K. Concern or Apathy: The Attitude of the Public toward Urban Air Pollution. *J. Risk Res.* **2017**, *20*, 482–498. [\[CrossRef\]](#)
18. Hankook Research. *Monthly Report, March 2018*; Hankook Research: Seoul, Korea, 2018.
19. World Health Organization. *Personal Interventions and Risk Communication on Air Pollution: Summary Report of WHO Expert Consultation, 12–14 February 2019, Geneva, Switzerland*; World Health Organization: Geneva, Switzerland, 2020; ISBN 978-92-4-000027-8.
20. Balram, D.; Lian, K.-Y.; Sebastian, N. Air Quality Warning System Based on a Localized PM2.5 Soft Sensor Using a Novel Approach of Bayesian Regularized Neural Network via Forward Feature Selection. *Ecotoxicol. Environ. Saf.* **2019**, *182*, 109386. [\[CrossRef\]](#)
21. Sharma, E.; Deo, R.C.; Prasad, R.; Parisi, A.V. A Hybrid Air Quality Early-Warning Framework: An Hourly Forecasting Model with Online Sequential Extreme Learning Machines and Empirical Mode Decomposition Algorithms. *Sci. Total Environ.* **2020**, *709*, 135934. [\[CrossRef\]](#)
22. Yang, G.; Lee, H.; Lee, G. A Hybrid Deep Learning Model to Forecast Particulate Matter Concentration Levels in Seoul, South Korea. *Atmosphere* **2020**, *11*, 348. [\[CrossRef\]](#)
23. Saberian, S.; Heyes, A.; Rivers, N. Alerts Work! Air Quality Warnings and Cycling. *Resour. Energy Econ.* **2017**, *49*, 165–185. [\[CrossRef\]](#)
24. Zhou, X.; Santana Jiménez, Y.; Pérez Rodríguez, J.V.; Hernández, J.M. Air Pollution and Tourism Demand: A Case Study of Beijing, China. *Int. J. Tour. Res.* **2019**, *21*, 747–757. [\[CrossRef\]](#)
25. Yeo, M.; Kim, Y. Trends of the PM10 concentrations and high PM10 concentration cases by region in Korea. *Part. Aerosol Res.* **2019**, *15*, 45–56. [\[CrossRef\]](#)
26. Byun, S.; Kim, S.-Y. Has Air Pollution Concentration Increased over the Past 17 Years in Seoul, South Korea? The Gap between Public Perception and Measurement Data. *J. Korean Soc. Atmos. Environ.* **2020**, *36*, 240–248. [\[CrossRef\]](#)

-
27. Lee, J.H.; Kim, M.Y.; Kim, Y. Spatial Panel Analysis for PM2.5 Concentrations in Korea. *J. Korean Data Inf. Sci. Soc.* **2017**, *28*, 473–481.
 28. Yoon, S.; Kim, M. Topic Modeling on Fine Dust Issues Using LDA Analysis. *J. Energy Eng.* **2020**, *29*, 23–29. [[CrossRef](#)]
 29. Kim, Y.; Lee, H.; Lee, H.; Jang, Y. A Study of the Public's Perception and Opinion Formation on Particulate Matter Risk. *Korean J. Commun. Inf.* **2015**, *72*, 52–91.
 30. McCombs, M. *Setting the Agenda: The Mass Media and Public Opinion*; Blackwell Publishing Inc.: Hoboken, NJ, USA, 2004; ISBN 978-0-7456-2312-2.
 31. Cha, H.-J.; Tian, Z.M.; Kweon, S.H. A Study on the Intermedia Network Agenda Setting on PM Issues: Focusing on the Network Agenda Setting between Media Reports and Naver Blogs. *J. Cybercommun. Acad. Soc.* **2020**, *37*, 5–52. [[CrossRef](#)]
 32. Choi, Y.; Yoon, H.; Kim, D. Where Do People Spend Their Leisure Time on Dusty Days? Application of Spatiotemporal Behavioral Responses to Particulate Matter Pollution. *Ann. Reg. Sci.* **2019**, *63*, 317–339. [[CrossRef](#)]
 33. Lee, K.-K.; Park, Y.; Han, S.-P.; Kim, H.C. The Alerting Effect from Rising Public Awareness of Air Quality on the Outdoor Activities of Megacity Residents. *Sustainability* **2020**, *12*, 820. [[CrossRef](#)]