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Spatial and Temporal Exposure Assessment to $PM_{2.5}$ in a Community Using Sensor-Based Air Monitoring Instruments and Dynamic Population Distributions

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Abstract: This research was to conduct a pilot study for two consecutive days in order to assess fine particulate matter ($PM_{2.5}$) exposure of an entire population in a community. We aimed to construct a surveillance system by analyzing the observed spatio-temporal variation of exposure. Guro-gu in Seoul, South Korea, was divided into 2,204 scale grids of 100 m each. Hourly exposure concentrations of $PM_{2.5}$ were modeled by the inverse distance weighted method, using 24 sensor-based air monitoring instruments and the indoor-to-outdoor concentration ratio. Population distribution was assessed using mobile phone network data and indoor residential rates, according to sex and age over time. Exposure concentration, population distribution, and population exposure were visualized to present spatio-temporal variation. The $PM_{2.5}$ exposure of the entire population of Guro-gu was calculated by population-weighted average exposure concentration. The average concentration of outdoor $PM_{2.5}$ was 42.1 μg/m^3, which was lower than the value of the beta attenuation monitor measured by fixed monitoring station. Indoor concentration was estimated using an indoor-to-outdoor $PM_{2.5}$ concentration ratio of 0.747. The population-weighted average exposure concentration of $PM_{2.5}$ was 32.4 μg/m^3. Thirty-one percent of the population exceeded the Korean Atmospheric Environmental Standard for $PM_{2.5}$ over a 24 h average period. The results of this study can be used in a long-term aggregate and cumulative $PM_{2.5}$ exposure assessment, and as a basis for policy decisions on public health management among policymakers and stakeholders.

Keywords: exposure surveillance system; fine particulate matter; dynamic population distribution; population exposure; time–activity pattern

1. Introduction

Fine particulate matter ($PM_{2.5}$) is an air pollutant that is classified as a Group 1 carcinogen by the International Agency for Research on Cancer [1]. It can cause various adverse health effects. The World Health Organization suggested that a 10 μg/m^3 increased concentration of $PM_{2.5}$ was associated with a

6–13% increase in long-term exposure risk of cardiopulmonary disease mortality rate [2]. Also, Di et al. accounts for a 7.3% increase in all-cause mortality [3]. A $PM_{2.5}$ exposure assessment in a community such as an industrial complex is crucial in terms of public health since it can provide the data required to develop a suitable management plan [4].

The necessity of an exposure surveillance system is emerging in the field of exposure science. An exposure or health surveillance system can be defined as a monitoring system that tracks aggregate and cumulative exposure of the human body to the hazardous agent, and enables assessment of the population exposure, considering the spatial and temporal variation of air pollutants (e.g., emission source, reaction, and deposition) and the population's time-activity pattern [5–8]. Although the Korean Ministry of Environment provides information for $PM_{2.5}$ measured by beta attenuation monitor (BAM), these data cannot reflect the actual exposure of the population [9,10]. An exposure surveillance system could be constructed with a sustainably gathered information about exposure concentration and population dynamics. Most recently, exposure assessments using low-cost sensors and mobile phone data have been performed [11–13].

When assessing population exposure, if the study area is divided into high-resolution grids and the results are summed, a reliable exposure assessment can be performed. To assess population exposure, it is necessary to gather information about the distribution of exposure concentration and population to incorporate the exposure concentrations and time-activity pattern. Many studies have suggested the relationship between $PM_{2.5}$ concentrations and public health by analyzing long-term $PM_{2.5}$ concentrations [14–16]. However, they mainly focused on outdoor exposure concentrations and only used data from the fixed-air monitoring stations. Since people spent most of their time indoors, indoor air quality should also be considered when assessing exposure to air pollutants. Zhang et al. assessed population exposure with relation to human cumulative exposure, using interpolation and population distribution based on census data [17]. There are limitations to assessing population exposure using the population distribution based on census data, because they were constructed with low resolution. Another technique is with the use of mobile phones to estimate population distribution [18]. The exposure of the entire population in a community can be estimated by population-weighted average exposure concentration (PWAC) [19]. PWAC is a method performed by weighting the rate of the number of people in a unit area—divided by the grid—per entire area to the exposure concentration in the unit area. By summing up all of PWAC, it is possible to assess the exposure of the entire population.

In this study, a pilot test was conducted to assess the population exposure of a community using the concentration of $PM_{2.5}$ measured by sensor-based air monitoring instrument (SAMI) and the population distribution using mobile phone data.

2. Methods

2.1. Subject Area

The research was conducted on 1 and 2 October 2019 for 48 h in Guro-gu. Guro-gu is one of the 25 districts of Seoul, which is the capital city of Republic of Korea. It had a population of 435,560 in 2019, accounting for 4.5% of the population of Seoul, with an area of 20.12 km^2. We divided this study area by 2204 grids of 100 m square (Figure 1).

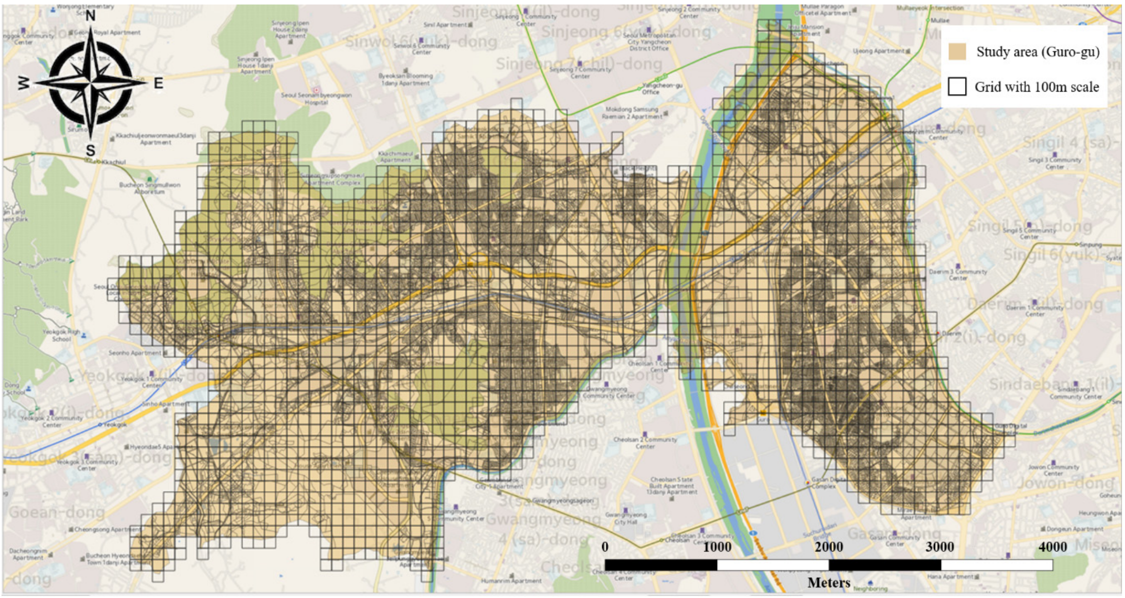
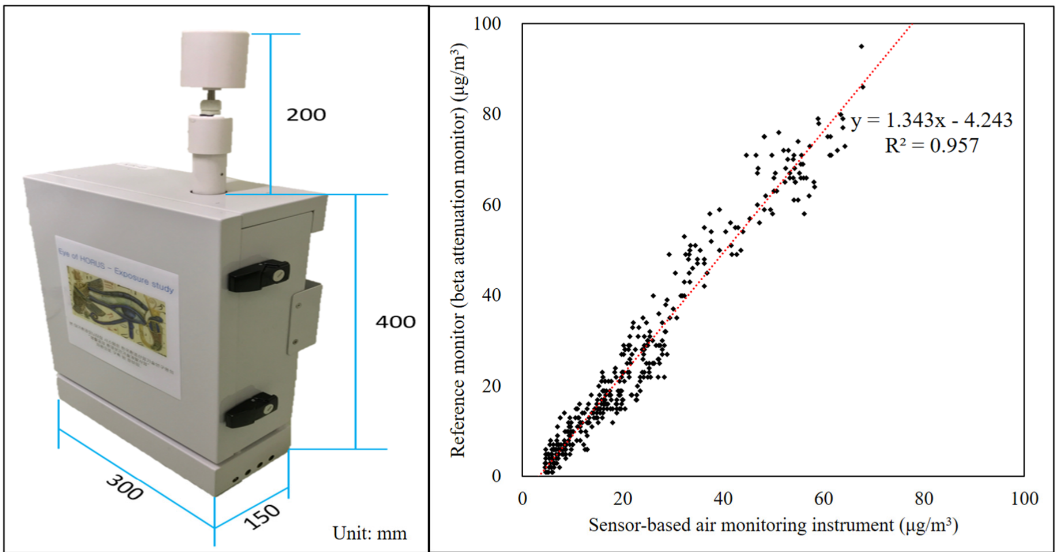


Figure 1. Study area divided by a 100 m scale grid.

2.2. Indoor and Outdoor Exposure Model

We installed 24 SAMIs with approximately 1 km^2 scale resolution in Guro-gu. The SAMIs used in this study consisted of a set of sensors that can measure $PM_{2.5}$ concentration, temperature, and relative humidity. The model used was designed to maintain a temperature of 20–30 °C and relative humidity of less than 70%, with a pretreatment control device and an integrated system. The detailed specification of the SAMI is shown in Figure 2. The $PM_{2.5}$ concentrations measured by the SAMIs were collected every minute and transmitted to the G-Cloud (Government Cloud), which is a cloud computing service developed for the Korean government's public institution launched in 2012 [20].



$PM_{2.5}$ sensor Model (Country)	SD-16C (South Korea)
Measuring Principle	Light scattering spectrometer
Particle size range	0.3 μm-25 μm
Reproducibility	± 5%
Flow rate	0.5 L/min
Resolution	0.1 μg/m³

Figure 2. Specification of sensor-based air monitoring instrument.

The outdoor $PM_{2.5}$ concentrations of each grid were modeled by inverse distance weighting (IDW) method using SAMIs (Equation (1)):

$$z_p = \frac{\sum_{i=1}^{n} z_i w_i}{\sum_{i=1}^{n} w_i} \quad (1)$$

where z_p is the estimated concentration at site p, z_i is the measured concentration at site i, w_i is the weight of interpolation, and n is the number of SAMI used for interpolation

To estimate indoor $PM_{2.5}$ concentration, we applied an indoor-to-outdoor (I/O) $PM_{2.5}$ concentration ratio [21]. The I/O ratio of Guro-gu's indoor buildings when adapted was 0.747, which is a result of simulating standardized the time–activity patterns of the general households in Seoul [22,23].

2.3. Population Distribution

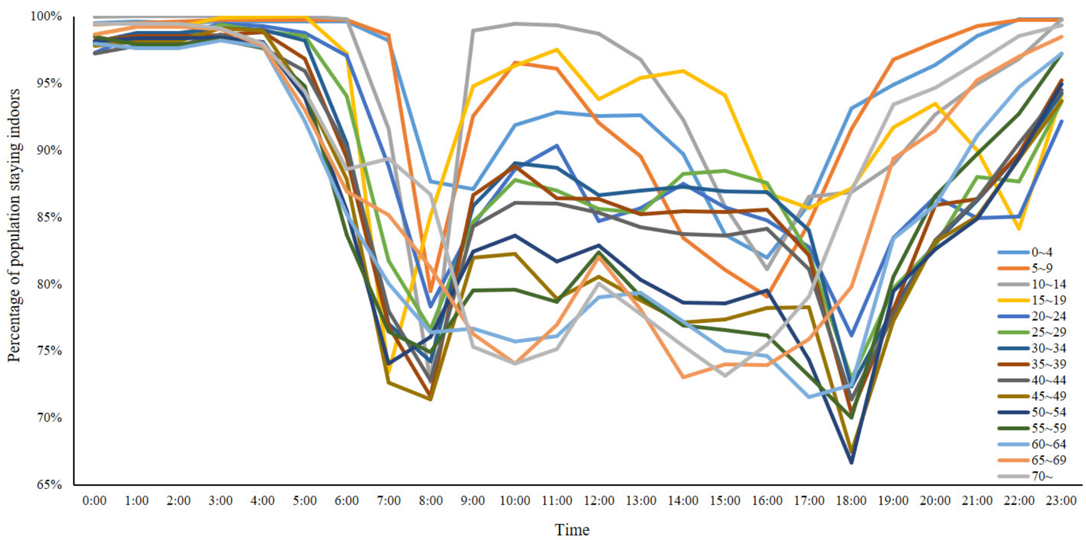
Population distribution of Guro-gu was determined by the number of people in each grid estimated by a pilot pattern cell database (pCell DB). The pCell method uses one of the tracking locations of mobile phone user when the device cannot receive a GPS signal. It uses the positioning solution of the pattern matching method. The program had patterned station coordinates of the propagation environment of the service area in the database, and so determined the location of mobile phone users by matching the propagation characteristics with database. The pCell data from wireless communication systems identified the number of people without personal information except age and sex within a grid (100 m × 100 m), defined based on the coverage of signals from the base stations. The pCell data were the results that mobile network operators have been observing from each wireless tower signal coverage periodically. The size of each pCell population per each hour was estimated by mapping the coverage of whole wireless tower and mobile phone reports, which include the connecting tower identifications (IDs). Moreover, the pCell data used an algorithm approved by Korean National Statistical Office for converting mobile network operator population to whole community population. The estimated population distribution was averaged by the number of people in a grid for one hour, and sorted by dividing the population into five years of sex and age.

To estimate the population distribution in indoors and outdoors, we used time-activity analysis results that surveyed subjects under age 10 [24]. The subjects of the survey were selected across the nation using a stratified sampling method according to square root proportional allotment. It targeted 922 subjects by season (spring, summer, fall, and winter) from 2013 to 2014. The survey was conducted for two consequence days. The subjects were required to record their behavior and whether their locations were indoors or outdoors in the time-activity diary. In the case of the subjects who were too young to record their diary, the subjects' parents recorded the results.

In the case of subjects age 10 or older, we used a Time-Use Survey dataset of 3,984 residents of Seoul. These data were published in 2016, and were downloaded from the Korean National Statistical Office's website (http://kostat.go.kr/portal/korea/kor_nw/1/6/4/index.board). The Time-Use Survey is a national standardized survey that is conducted every five years. It records the behavior and location of the subjects in a time-activity diary. Participants were recruited across the country using a stratified sampling method according to a square root proportional allotment considering sex and age. The indoor microenvironments of the subjects were categorized into eight microenvironments: home, workplace, school, another house, bar or restaurant, other indoor places, places for walking (outdoors), and transport. For the Time-Use Survey data, the times spent in each microenvironment were not classified as either indoor or outdoor environments. Therefore, the indoor staying rate of each microenvironment presented in the Korean Exposure Factor Handbook was applied to the time spent in each microenvironment [25]. Table 1 presents the indoor staying rates according to the microenvironments. We applied these data together with that from Time-Use Survey to show the total indoor staying rates according to age, sex, and time. The trend is shown in Figure 3. We calculated the number of people indoors and outdoors from each grid by applying the staying rate of Figure 3 to the population distribution data.

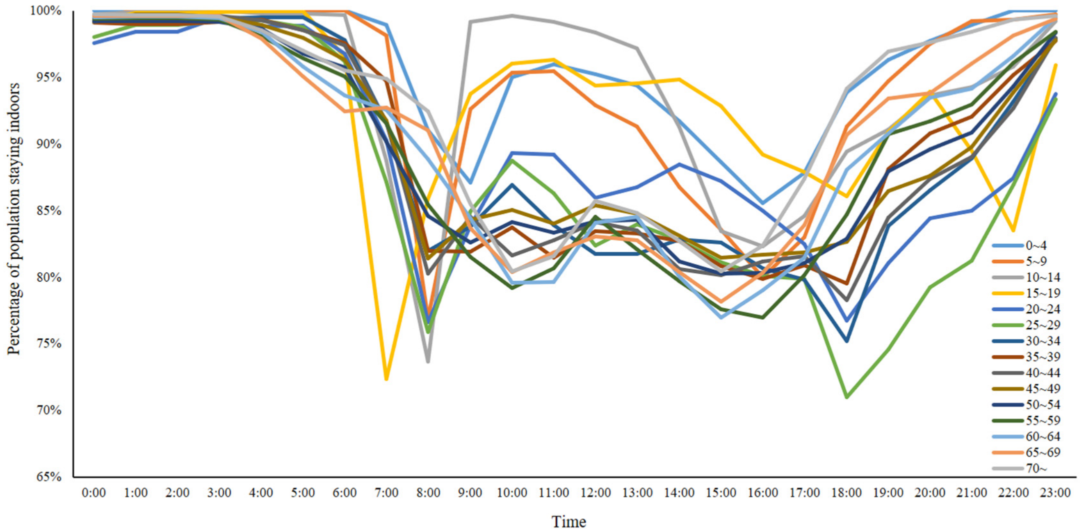
Table 1. Rate of staying indoors according to microenvironments by sex and age.

Sex	Age	Indoor (%)					
		Home	Workplace or School	Other House	Restaurant or Bar	Other Indoors	Transport
Male	19–24	99.86	95.18	100.00	99.25	87.87	100
	25–34	99.97	94.98	100.00	94.24	83.91	
	35–44	99.93	96.66	100.00	96.15	74.19	
	45–54	99.95	95.23	100.00	96.76	50.60	
	55–64	99.82	92.77	100.00	94.92	52.57	
	65–74	99.80	89.96	98.78	95.71	52.51	
	<75	99.46	57.14	100.00	97.87	50.86	
Female	19–24	99.94	97.45	100.00	97.99	83.27	
	25–34	100	98.64	100.00	92.46	32.14	
	35–44	99.95	98.02	100.00	98.41	49.04	
	45–54	99.91	99.77	100.00	97.77	55.70	
	55–64	99.95	95.59	100.00	99.62	55.33	
	65–74	99.82	91.58	96.88	94.12	70.64	
	<75	99.76	100.00	100.00	100.00	59.60	



a. Male

Figure 3. *Cont.*



b. Female

Figure 3. Percentage of population staying indoors by sex, age, and the time of the day in weekday. (**a**) Male (**b**) Female

2.4. Population Exposure

We assessed the population exposure using $PM_{2.5}$ concentrations and the population distribution of each grid. The assessment of exposure was performed using the equation below (Equation (2)). To map the outdoor $PM_{2.5}$ concentration, population distribution, and population exposure, we used Quantum GIS software version 3.16.

$$\text{Population Exposure} = c_i p_i + c_o p_o \tag{2}$$

where c_i is the indoor exposure concentration, c_o is the outdoor exposure concentration, p_i is the number of people indoors, and p_o is the number of people outdoors.

To assess the exposure to $PM_{2.5}$ of the entire population of Guro-gu, we calculated the PWAC by weighting the number of people to the exposure concentration in each grid (Equation (3)). To assess population exposure to $PM_{2.5}$ probabilistically, we calculated the rate with the use of frequency analysis and histogram. The resulting rate of exposure exceeded the Korean Atmospheric Environmental Standard. We excluded the grid with a PWAC of zero (resulted from zero population) in the frequency analysis.

$$\text{PWAC} = \sum\nolimits_{i=i}^{n} \frac{c_i p_i + c_o p_o}{p_i p_o} \tag{3}$$

where, PWAC is the population weighted average concentration (μg/m^3), n is the number of the grid, c_i is the indoor exposure concentration in grid n, c_o is the outdoor exposure concentration in grid n, p_i is the number of people indoors in grid n, p_o is the number of people outdoors in grid n.

3. Results

3.1. Indoor and Outdoor Exposure Model

The temporal and spatial variations of the outdoor concentration of $PM_{2.5}$ for 2 days are presented in Figures 4 and 5. These variations in concentration are further illustrated as an animation in Figure S1. The temporal variation presented the entire average outdoor concentration in Guro-gu, modeled by SAMI and measured by an urban air monitoring station (UAMS) using the beta attenuation monitor. The average outdoor $PM_{2.5}$ concentration in Guro-gu for 2 days was 42.1 μg/m^3, and the standard deviation according to time and location was 27.7 μg/m^3 and 22.7 μg/m^3, respectively. The average concentration of UAMS for 2 days was 16.4 ± 10.5 μg/m^3. The correlation between the modeled outdoor average concentration of the entire Guro-gu and UAMS is presented in Figure 6. The correlation coefficient (R^2) was 0.8604, the slope was 0.3565, and the intercept was 1.0806.

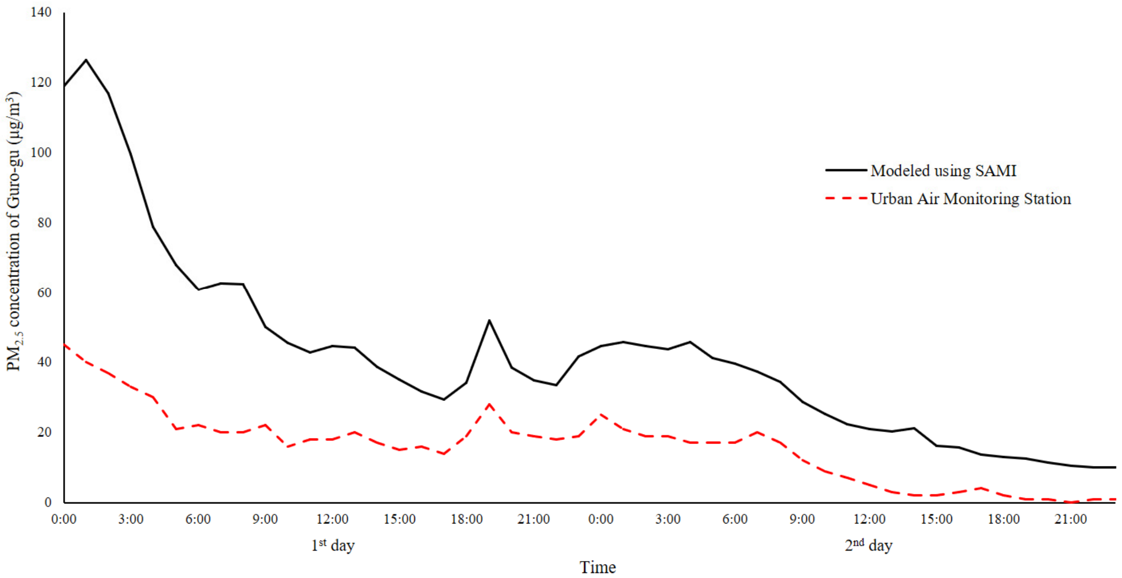


Figure 4. Comparison of outdoor fine particulate matter ($PM_{2.5}$) concentrations modeled by a sensor-based air monitoring instrument (SAMI) and measured by an urban air monitoring station over time.

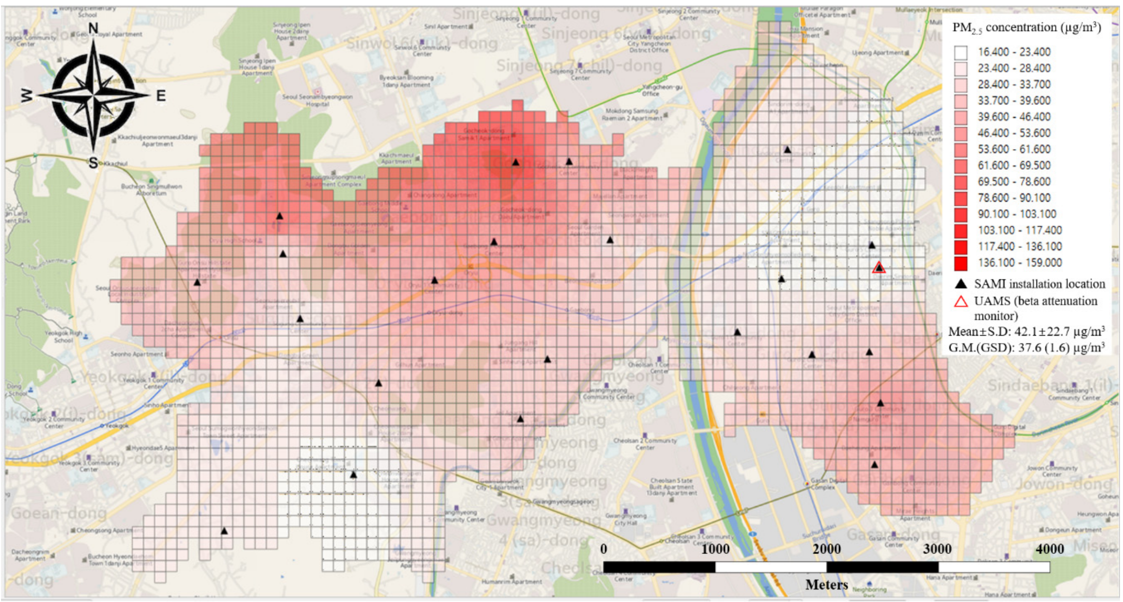


Figure 5. Spatial variation of modeled outdoor $PM_{2.5}$ concentration in Guro-gu.

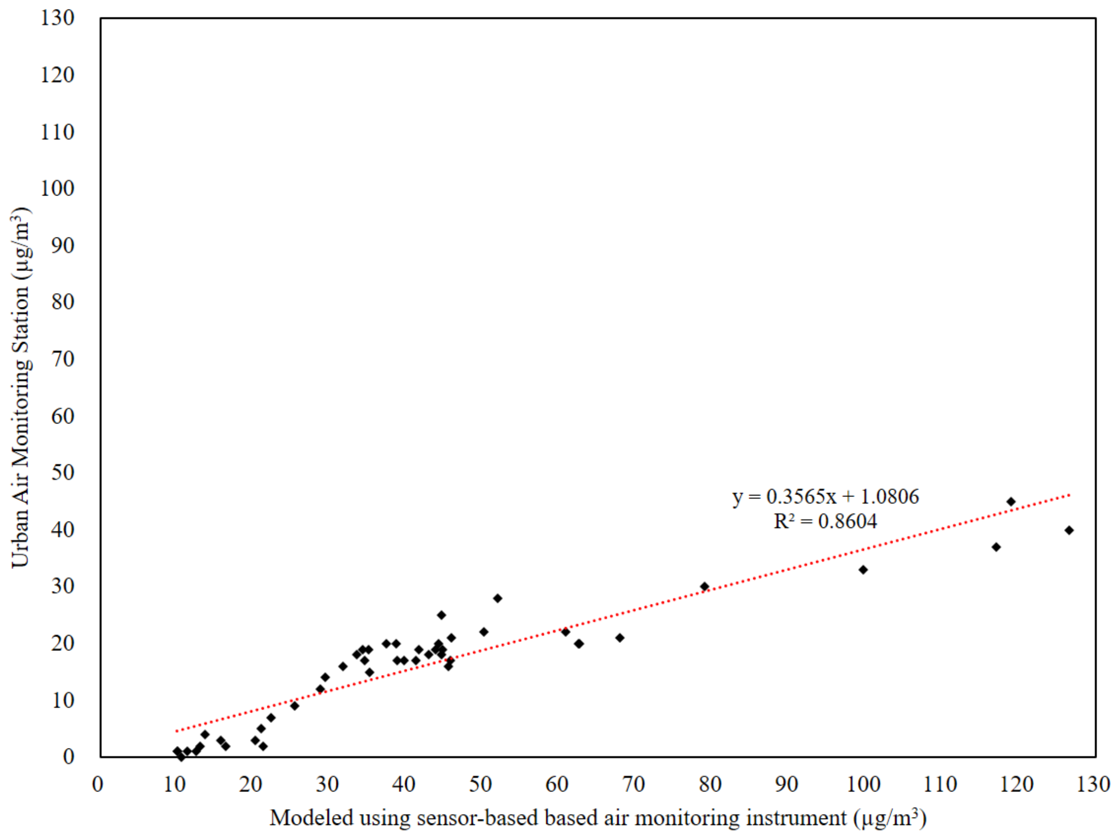


Figure 6. Correlation between outdoor $PM_{2.5}$ concentrations measured by the Urban Air Monitoring Station and modeled by sensor-based air monitoring instruments in Guro-gu.

3.2. Population Distribution

The temporal and spatial variations of the population in Guro-gu are presented in Figures 7 and 8. For further illustration of the spatial and temporal variations of the total number of people in Guro-gu, we provided an animation as Figure S2.

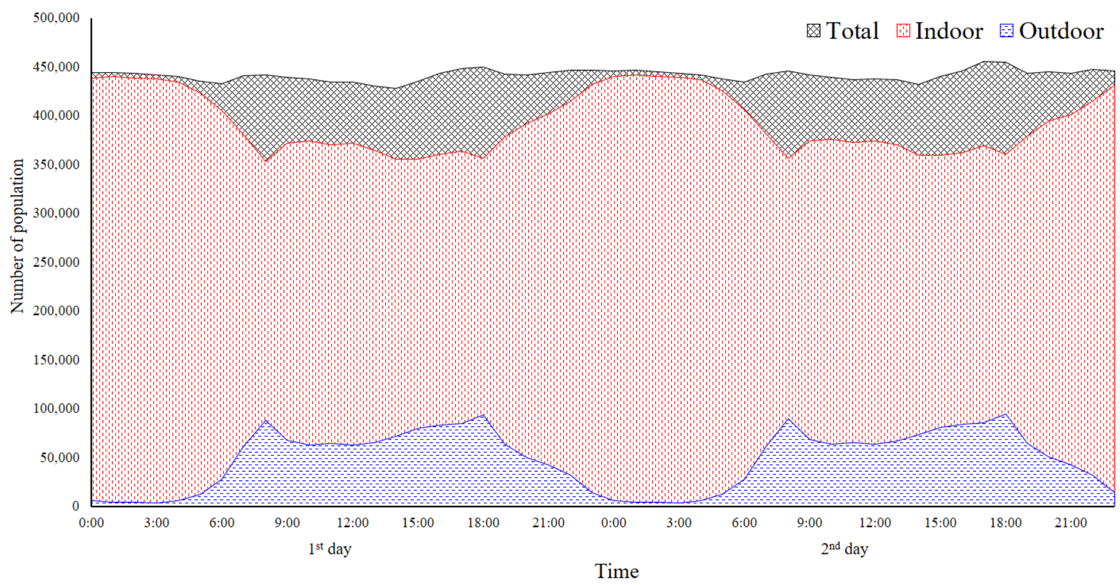


Figure 7. Temporal variation of the total number of people in Guro-gu.

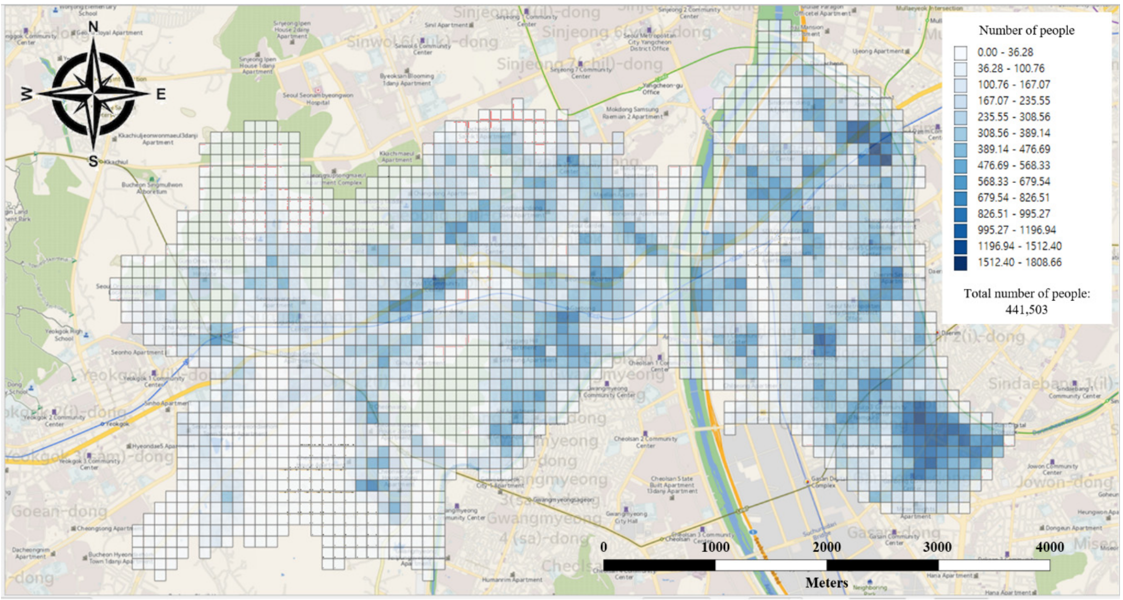


Figure 8. Spatial variation of the total number of people in Guro-gu.

3.3. Population Exposure

Figure 9 presents the population exposure to $PM_{2.5}$ of Guro-gu. The PWAC of the entire population was 32.4 μg/m^3. Also, an animation showing the spatial and temporal variations is presented in Figure S3.

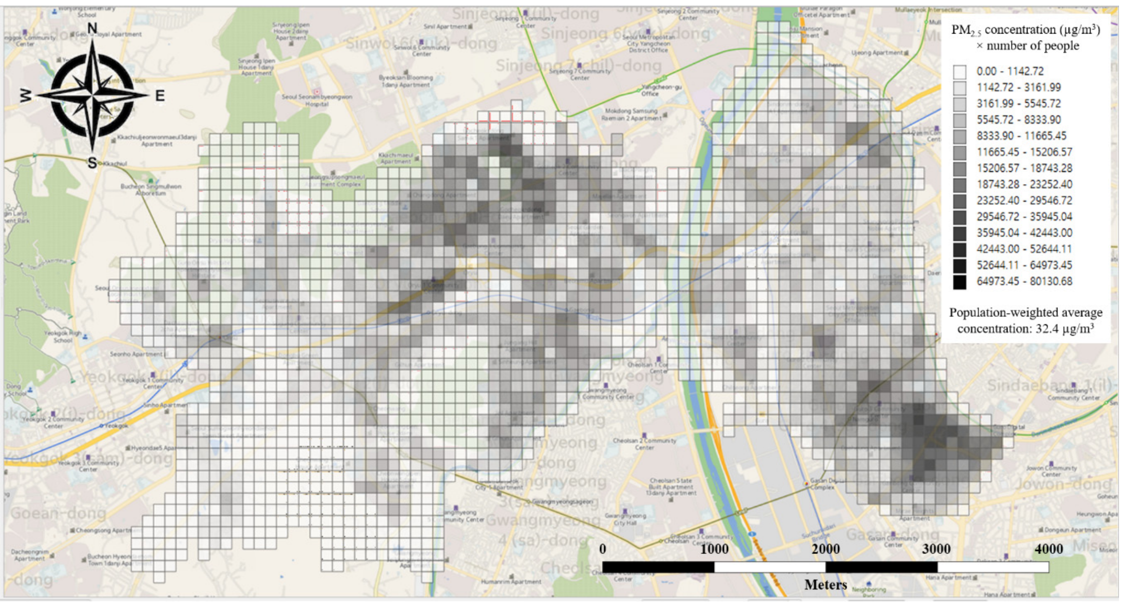


Figure 9. Population exposure to $PM_{2.5}$ in Guro-gu.

The histogram of the $PM_{2.5}$ PWAC is shown in Figure 10. Aout 97.5% and 31.4% of the studied population exceeded the Korean Atmospheric Environmental Standard for $PM_{2.5}$ for both annual (35 μg/m^3) and 24 h (15 μg/m^3) averages, respectively.

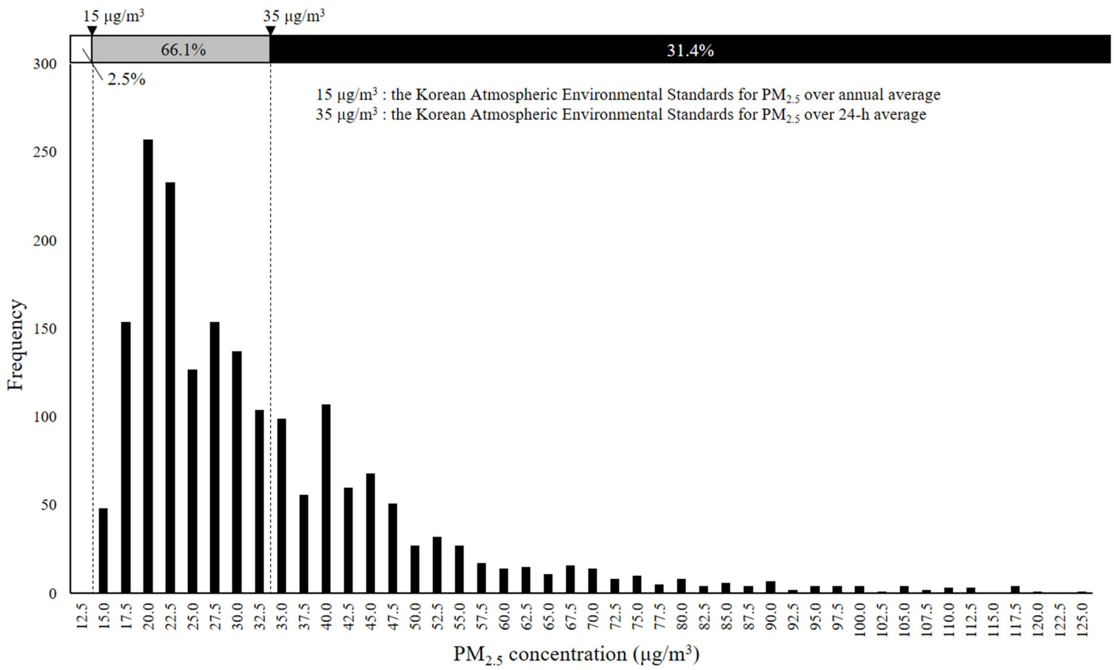


Figure 10. Histogram of population-weighted average exposure concentrations of $PM_{2.5}$.

4. Discussion

The $PM_{2.5}$ exposure of the entire population was assessed by constructing an exposure surveillance system considering spatio-temporal variations. The exposure assessment for the entire population was reliable because the concentration of $PM_{2.5}$ was modeled by a sensor-based air monitoring instrument that captures real-time measurements, data communication, and population distribution representing population dynamics. It was obtained by using a mobile phone. There were limitations in estimating indoor concentration and the distribution of the population indoors and outdoors. For instance, the I/O ratio was applied to estimate indoor $PM_{2.5}$ concentrations, while the indoor staying rates according to age and sex were applied to indoor and outdoor population distributions. However, these could be representatives because the I/O ratio was a result of simulated standardized time-activity patterns of general Korean households, and the indoor staying rates by time were assessed based on demographical characteristics.

The $PM_{2.5}$ concentration of Guro-gu was modeled using the IDW method and I/O ratio based on measurements by SAMIs. The modeled outdoor average concentration of $PM_{2.5}$ in the entire Guro-gu was relatively lower than the one measured by the UAMS. It was determined that the concentration of $PM_{2.5}$ near the UAMS was relatively low, as shown in the spatial variation (Figure 5). The UAMS that offers a representative concentration of $PM_{2.5}$ of the local area has limitations to detect spatial variation, such as local air pollutant sources [26,27]. Recently, exposure assessment studies have widely been performed using low-cost sensors [28–30]. This methodology enables exposure assessment to air pollutants with relatively low cost and high resolution, and eases data management by using information and communication technology like wireless fidelity (WiFi) and long-term evolution (LTE) networks [31–34]. The IDW model used in this study to estimate $PM_{2.5}$ concentration is one of the geostatistical models, which is more suitable for this study, in which multiple measurement spots are distributed, than the source-based model [35]. Recently, the methodologies using machine learning or deep learning technology to estimate ambient air pollutant concentrations have been widely used [36]. According to Yang et al., artificial intelligence technology and statistical models have been used as exposure models of air pollutants, and statistical models have shown relatively high accuracy until now [37].

The average I/O ratio of $PM_{2.5}$ concentrations in apartment houses was applied to estimate indoor $PM_{2.5}$ concentration. The I/O ratio in other microenvironments could be different [38]. However, the I/O ratio in this study and the previous findings for 4,403 Chinese who spent time at home were similar at 0.73 ± 0.54 [39]. On the other hand, the average I/O ratio of an urban area in India was 0.92, which is higher than our current finding. The difference may be attributed to the effect of indoor smoking [40]. The concentration of indoor air pollutant can be affected by the outdoor environment [41,42]. Also, estimating the indoor concentrations of indoor air pollutants using the I/O ratio may be limited when other indoor sources exist [43]. The indoor concentration in various microenvironments can be modeled by a statistical method in a further study, by installing SAMIs indoors. Benammar et al. suggested indoor air quality monitoring systems using wireless sensor networks [44], and Wei et al. predicted indoor air quality using machine learning and statistical model [45]. We envision an advantage in the monitoring and modeling of indoor microenvironments in further studies, because the systems were installed in cooperation with the local government, and the places of SAMIs installed in this study were where people spend most of their time such as school, subway stations, and multi-use facilities, as well as houses.

In terms of spatial variation of the population of Guro-gu, we observed that the number of people increased between 8:00 and 18:00. This variation could be explained by the concentration of the population in Guro Station and Guro Digital Complex during rush hour. In particular, the Guro Digital Complex has a downtown area where bars and restaurants are concentrated. These results are also shown in Figure S2. When assessing the population exposure to air pollutants, exposure is generally assessed through analysis of time-activity pattern of individuals or groups. South Korea offers a time-activity pattern through Korean Exposure Factor Handbook [25], and the U.S. Environmental Protection Agency (EPA) also presents a Consolidated Human Activity Database [46]. While these data could present representative time-activity patterns, there is a need to evaluate the population dynamics. To assess population dynamics, the studies using features of mobile phones such as WiFi and accelerometers [47–49] as well as GPS [50,51] have been conducted. Breen et al. developed a smartphone application named MicroTrac to assess individual's time–activity patterns [52]. However, these methodologies may only be suitable for personal exposure assessment, and not for population exposure assessment, because they are only applicable to voluntary participants such as citizen scientists.

In contrast, the geographical distribution of mobile device users is received by encrypted code because the pCell data in wireless communication systems identifies the number of people based on the coverage of signals from base stations. The location information of the population can be captured based on base stations without GPS data and consent procedures for personal information. In addition, determining the number of people using GPS is less accurate because it is difficult to apply indoors. The pCell method, however, has high accuracy as it can identify all location information of mobile devices that are registered in the mobile communication system. Since there are 582 base stations of SK telecom in Guro-gu, it can be reliable to count the number of people. Currently, although population dynamic data through the pCell method have not been available in real time, they can be obtained for public purposes within one month. Considering that the penetration rate of mobile phones as of 2017 is 94% in Korea [53], it is clear that this is a novel approach in assessing population dynamics.

The population exposure in Guro-gu was concentrated in densely populated locations with high $PM_{2.5}$ concentration. Based on these results, the area of concern that indicate high exposure to $PM_{2.5}$ can be identified and suitable management plans will be established. Zhang et al. conducted a population exposure assessment about human cumulative exposure through interpolation techniques and population distribution using census data for Beijing [17]. However, their population distribution was divided into only two areas. Also, Picornell et al. conducted an exposure assessment considering population dynamics using mobile phone data with 1 km resolution, and compared it with census-based results [18]. While most of these studies considered only the exposure outdoors and discounted indoor and outdoor population distribution, this study assessed indoor exposure to $PM_{2.5}$ with high resolution of 100 m grids through representative data of Korea

The PWAC of Guro-gu was 32.4 μg/m^3, and 31.4%, and 97.5% of the population exceeded the Korean Atmospheric Environmental Standard for $PM_{2.5}$ over annual (35 μg/m^3) and 24 h (15 μg/m^3), respectively. Therefore, it can be explained that exposure management to $PM_{2.5}$ could be required. This result was lower than 52.7 μg/m^3, which was the annual PWAC of China [54]. Aunan et al. suggested that the integrated population-weighted exposure to ambient air in the urban and rural areas was 62 μg/m^3 and 53 μg/m^3, respectively [55]. In Germany, the population-weighted exposure was 10.52 μg/m^3 [56].

The $PM_{2.5}$ exposure surveillance system constructed in this study has been measuring and estimating exposure concentrations of $PM_{2.5}$ in Guro-gu. These accumulated data shows that a reliable prediction will be possible through advanced methods. However, concerns about personal data privacy could be raised with the use of mobile phone data in the assessment of population dynamics. If anonymity can be guaranteed in public health studies, these concerns may be resolved. The results of this study can be used in long-term aggregate and cumulative $PM_{2.5}$ exposure monitoring studies; they can be used as a basis to help make policy decisions for public health management among policymakers and stakeholders.

5. Conclusions

The $PM_{2.5}$ exposure of the entire population in a community could be assessed by establishing an exposure surveillance system using sensor-based air monitoring and dynamic population. This study presented a methodology for assessing exposure to population groups using the latest technologies such as sensor, internet of things (IoT) and telecommunications. By taking into account the spatio-temporal variation of $PM_{2.5}$ concentration and population dynamics, the aggregate and cumulative population exposure to $PM_{2.5}$ could be assessed, and appropriate management plans be proposed by identifying areas of concern.

Supplementary Materials: The following are available online at http://www.mdpi.com/2073-4433/11/12/1284/s1: Figure S1: Spatio-temporal variation of outdoor $PM_{2.5}$ concentrations; Figure S2: Spatio-temporal variation of population distribution; Figure S3: Spatio-temporal variation of population exposure to $PM_{2.5}$.

Author Contributions: Writing—original draft preparation, J.P. and W.J.; methodology, M.C.; review and editing, J.L. and H.L.; investigation and supervision, S.S. and C.L.; supervision, conceptualization, writing, review, and editing, W.Y. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this article.

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