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Assessment of sociodemographic disparities in environmental exposure might be erroneous due to neighborhood effect averaging: Implications for environmental inequality research

Junghwan Kim[a], Mei-Po Kwan[b,c,*]

[a] Department of Geography and Geographic Information Science, University of Illinois at Urbana-Champaign, Urbana, IL 61801, USA
[b] Department of Geography and Resource Management and Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, Hong Kong, China
[c] Department of Human Geography and Spatial Planning, Utrecht University, Utrecht, The Netherlands

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ABSTRACT

The neighborhood effect averaging problem (NEAP) is a major methodological problem that might affect the accuracy of assessments of individual exposure to mobility-dependent environmental factors (e.g., air/noise pollution, green/blue spaces, or healthy food environments). Focusing on outdoor ground-level ozone as a major air pollutant, this paper examines the NEAP in the evaluation of sociodemographic disparities in people's air pollution exposures in Los Angeles using one-day activity-travel diary data of 3790 individuals. It addresses two questions: (1) How does the NEAP affect the evaluation of sociodemographic disparities in people's air pollution exposures? (2) Which social groups with high residence-based exposures do not experience neighborhood effect averaging? The results of our spatial regression models indicate that assessments of sociodemographic disparities in people's outdoor ground-level ozone exposures might be erroneous when people's daily mobility is ignored because of the different manifestations of neighborhood effect averaging for different social/racial groups. The results of our spatial autologistic regression model reveal that non-workers (e.g., the unemployed, homemakers, the retired, and students) do not experience *downward averaging*: they have significantly lower odds of experiencing *downward averaging* that could have attenuated their high exposures experienced in their residential neighborhoods while traveling to other neighborhoods (thus, being doubly disadvantaged). Therefore, to avoid erroneous conclusions in environmental inequality research and ineffective public policies, it would be critical to take the NEAP into account in future studies of sociodemographic disparities related to mobility-dependent environmental factors.

1. Introduction

In recent decades, air pollution exposure is one of the critical environmental factors that have significant negative impacts on people's health (Health Effects Institute, 2010). In the U.S., for instance, it is estimated that about 150 million people live in neighborhoods with unhealthy air quality (American Lung Association, 2020). Studies in health geography and public health have examined the adverse effects of air pollution exposure on human health (Mirabelli et al., 2015; Oudin et al., 2016). Furthermore, studies have investigated sociodemographic disparities in people's air pollution exposure, which may result in disparities in their health outcomes (e.g., Bell and Ebisu, 2012; Chakraborty, 2009; Clark et al., 2014; Houston et al., 2004).

For all studies that examine the sociodemographic disparities in people's air pollution exposure, one of the critical tasks is to accurately assess how and to what extent people are exposed to air pollution (Kwan, 2012). However, most previous studies assumed that people are static and remain in their residential neighborhoods and considered a fixed residential administrative unit (e.g., a census tract) as the most important and relevant neighborhood where air pollution affects people (Kwan, 2013, 2018a). In other words, previous studies have adopted the residence-based exposure assessment. For example, by focusing on people's residential census block groups in the U.S., Clark et al. (2014) concluded that the average exposure to outdoor nitrogen dioxide of the non-white population is significantly higher than that of the white population. Focusing on 6140 participants in the U.S., Hajat et al. (2013)

* Corresponding author. Department of Geography and Resource Management and Institute of Space and Earth Information Science, The Chinese University of Hong Kong, Shatin, Hong Kong, China.
E-mail addresses: jk11@illinois.edu (J. Kim), mpkwan@cuhk.edu.hk (M.-P. Kwan).

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concluded that people's family income level is significantly positively associated with a lower $PM_{2.5}$ exposure level in their home neighborhood.

Although these previous studies have provided a useful foundation for future works, we argue that evaluations of the sociodemographic disparities in people's air pollution exposures obtained by residence-based assessments might be inaccurate because of the neighborhood effect averaging problem (NEAP; Kwan, 2018b). The NEAP refers to the methodological problem that the assessment of people's exposure to mobility-dependent environmental factors (e.g., air/noise pollution, green/blue spaces, or healthy food environments) can be erroneous when people's mobility is ignored. Built upon the important conclusion of recent studies that residence-based and mobility-based individual air pollution exposures are significantly different (e.g., Dewulf et al., 2016; Setton et al., 2011; Shafran-Nathan et al., 2017; Park and Kwan, 2017; Yu et al., 2018), the NEAP suggests that residence-based individual exposure assessments (that overlook human daily mobility) may be inaccurate because they do not fully address neighborhood effect averaging in individual air pollution exposures (Kim and Kwan, 2019, 2021; Ma et al., 2020b; Tan et al., 2020).

Neighborhood effect averaging is the phenomenon that the distribution of mobility-based individual exposures (that consider people's daily mobility) is less deviated than that of residence-based individual exposures (Kwan, 2018b). In other words, individual exposures tend to converge toward the average exposure of a study area when people's daily mobility is considered. This is because each person's residence-based exposure can be attenuated or amplified by his/her daily mobility. Specifically, neighborhood effect averaging in individual air pollution exposures operates in the following two patterns: (1) *upward averaging* and (2) *downward averaging* (Fig. 1).

One pattern is the *upward averaging* (or amplification) of residence-based individual exposures (Kwan, 2018b). People who live in low pollution neighborhoods are highly likely to travel to high-pollution neighborhoods when undertaking their daily activities. This is because the probability density function (PDF) of air pollution levels typically follows a bell-shaped curve (e.g., Dewulf et al., 2016; Kim and Kwan, 2021; Nyhan et al., 2019). Therefore, their mobility-based exposure levels are higher than their residence-based exposure levels. The other pattern is the *downward averaging* (or attenuation) of residence-based individual exposures. People who live in high-pollution neighborhoods are highly likely to travel to low-pollution neighborhoods when undertaking their daily activities (Kwan, 2018b). Thus, their mobility-based exposure levels are lower than their residence-based exposure levels. As a result of these two patterns of neighborhood effect averaging, the distribution of mobility-based individual exposures is less deviated than that of residence-based individual exposures. A growing number of recent empirical studies have concluded that neighborhood effect averaging in individual air pollution exposures indeed exists across different study areas, including Belgium (Dewulf et al., 2016), China (Ma et al., 2020b; Yu et al., 2018), Israel (Shafran-Nathan et al., 2017), and the U.S. (Kim and Kwan, 2021). However, note that some people may not experience neighborhood effect averaging because they have only limited daily mobility or stay in their residential neighborhoods most of their time (Kim and Kwan, 2021; Ma et al., 2020b).

In this light, the neighborhood effect averaging problem (NEAP) further suggests that evaluations of the sociodemographic disparities in people's air pollution exposures that do not consider human daily mobility can be erroneous because residence-based exposures do not take neighborhood effect averaging into account. Specifically, the sociodemographic disparities in people's exposures evaluated by using their residence-based individual exposures can be overestimated. For example, assume that the average residence-based individual exposure of Group A is significantly lower than that of Group B. Assume also that members of both groups have unrestricted (typical) daily mobility. Due to neighborhood effect averaging, the average mobility-based individual exposure of Group A would tend to be higher than its average residence-based individual exposures (i.e., *upward averaging*). On the contrary, the average mobility-based individual exposure of Group B would tend to be lower than its average residence-based individual exposure (i.e., *downward averaging*). As a result, the difference in average exposures between Groups A and B based on mobility-based assessments tends to be smaller than that based on residence-based assessments. Therefore, the sociodemographic disparity in exposures between Groups A and B based on residence-based assessments can be overestimated, which is a manifestation of the NEAP.

Furthermore, the sociodemographic disparities in people's exposures evaluated by using the residence-based individual exposures can be underestimated. For instance, assume that the average residence-based individual exposure of Group C is similar to that of Group D and is higher than the regional average. Assume also that members of Group C have unrestricted (typical) daily mobility, while members of Group D

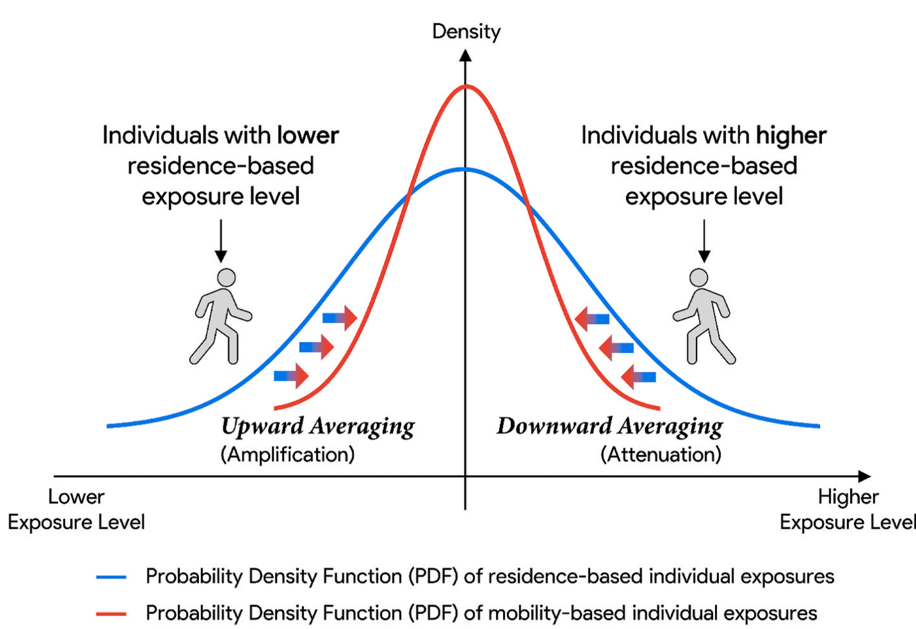

Fig. 1. A conceptual illustration of how neighborhood effect averaging operates in individual air pollution exposures.

have limited daily mobility. Because of neighborhood effect averaging, the average mobility-based individual exposure of Group C would tend to be lower than its average residence-based individual exposures (i.e., *downward averaging*). On the contrary, the average mobility-based and residence-based individual exposures of Group D would tend to be similar. This is because members of Group D have restricted daily mobility and thus do not experience neighborhood effect averaging as much as members of Group C (Kim and Kwan, 2021; Ma et al., 2020b). As a result, the difference in average exposures between Groups C and D based on the mobility-based assessment tends to be larger than that based on the residence-based assessment. Thus, the sociodemographic disparities in exposures between Groups C and D based on the residence-based assessments can be underestimated, which indicates the NEAP.

To sum up, when assessing the sociodemographic disparities in people's exposure to air pollution, ignoring human daily mobility (i.e., adopting the residence-based exposure assessment) may lead to the NEAP. The NEAP can be a serious methodological problem for studies that aim at investigating the sociodemographic disparities in people's air pollution exposures (Kwan, 2018b). Specifically, the NEAP suggests that using residence-based exposure assessments can lead to erroneous evaluations of the sociodemographic disparities in such exposures. Furthermore, given that current public health policies largely rely on residence-based exposure assessments, the NEAP implies that their evaluations of sociodemographic disparities in exposures may be erroneous, which might lead to inefficient allocations of public health policy efforts and resources (Caplin et al., 2019; Levy et al., 2001; Macintyre et al., 2001). However, few studies to date have provided an in-depth examination of the NEAP when evaluating the sociodemographic disparities in people's exposure to air pollution. To fill this gap, this research seeks to examine the NEAP in the evaluation of sociodemographic disparities in people's exposure to outdoor ground-level ozone by employing geographic information science methods and a one-day activity-travel diary dataset of 3790 people collected in Los Angeles, California.

Specifically, we ask the following two research questions: First, how does the NEAP affect the evaluation of sociodemographic disparities in people's air pollution exposures? In other words, how does ignoring human daily mobility lead to inaccurate assessment of the sociodemographic disparities in such exposures? Answering this question will not only provide a more realistic evaluation of sociodemographic disparities in people's air pollution exposures but also enrich our understanding of the role of human daily mobility and the NEAP in environmental inequality research.

Second, which social groups with high residence-based exposures do not experience neighborhood effect averaging? Neighborhood effect averaging suggests that, when people's residence-based exposure levels are high, their mobility-based exposure levels can be reduced due to *downward averaging*. However, there may be some people who do not experience *downward averaging* in exposures due to limited mobility and other reasons (Kim and Kwan, 2021; Ma et al., 2020b). In other words, their mobility-based exposure levels are equal to or even higher than their residence-based exposure levels, and this group of people can be referred to as the doubly disadvantaged in air pollution exposures (Elliott and Smiley, 2019; Sampson, 2019). Understanding why and how some people are doubly disadvantaged in air pollution exposures is critical because they need special policy interventions to mitigate their excessively high air pollution exposures.

Several important points are worth noting regarding this research. First, note that this research does not seek to examine whether sociodemographic disparities in people's exposure to outdoor ground-level ozone contribute to disparities in people's health outcomes (e.g., asthma rates). Instead, its goal is to provide a methodological investigation of the NEAP when evaluating the sociodemographic disparities in people's ozone exposures. In other words, this study seeks to investigate how ignoring human daily mobility may lead to inaccurate assessment of sociodemographic disparities in ozone exposures. Second, although some recent studies consider human daily mobility when investigating the sociodemographic disparities in air pollution exposures (e.g., Elliot and Smiley, 2019; Park and Kwan, 2020; Xu et al., 2019), this research is one of the first studies that investigate the NEAP in environmental inequalities. Third, although we focus only on outdoor ground-level ozone to measure air pollution exposures for methodological purposes, other air pollutants, such as particulate matter (PM), are also important in a comprehensive assessment of people's exposure to air pollution. Lastly, we assume that indoor ozone concentration level is the same as outdoor ozone concentration level because we do not have data on participants' indoor exposure.

2. Data and methods

2.1. Study area

The study area for this research is the Los Angeles Metropolitan Statistical Area (MSA), consisting of Los Angeles County and Orange County in California (Fig. 2). We choose MSA as the study scale because most people undertake their daily activities within the MSA boundary (U.S. Census Bureau, 2012). We focus on the Los Angeles MSA because of its infamously severe air pollution levels for decades (Houston et al., 2004; Jerrett et al., 2005a; Marshall et al., 2006). For instance, the average concentration of ground-level ozone of Los Angeles ranks first among about 200 metropolitan areas in the U.S. (American Lung Association, 2020). Besides, a recent public survey has revealed that 76% of the respondents living in the Los Angeles region think that air pollution is an important issue (Public Policy Institute of California, 2019). Since air pollution has been a serious public health issue in Los Angeles for decades, the results and implications of our research will be important for mitigating the sociodemographic disparities in people's air pollution exposures in Los Angeles.

2.2. Data

2.2.1. Individual one-day activity-travel diary data

We utilize individual one-day activity-travel diary data collected in the U.S. National Household Travel Survey (NHTS) California Add-on in 2017. Each participant's activity-travel diary contains detailed information about the geographic locations, types, start time, and duration of activities and transportation modes of trips during a report day. We use each participant's daily activity-travel diary data to create his/her daily space-time paths, which are then used to evaluate his/her exposure to air pollution over space and time. Among the 55793 NHTS participants, we focus on 3790 of them who undertook daily activities within the study area and provided complete sociodemographic information. Note that since the NHTS targets people from the entire California state, about 10% of the NHTS participants are selected for our study. These 3790 individuals of our subsample are divided into two groups: the first group consists of people who reported trips in one weekday (n = 2640), and the second group consists of people who reported trips in one weekend day (n = 1150). Note that each participant reported his/her activity-travel diary of either one weekday or one weekend day. The activity-travel diary data were accessed via a secure remote server of Transportation Secure Data Center because the data contain participants' confidential information (Transportation Secure Data Center, 2020). Table 1 compares key sociodemographic variables of the weekday and weekend subsample with those of the population in the Los Angeles MSA. Overall, the composition of the sociodemographic variables of the weekday subsample is similar to that of the weekend subsample. Also, the overall composition of the sociodemographic variables of our subsample is similar to that of the Los Angeles MSA. However, the mean age of the population in Los Angeles is lower than that of the subsample, and the percentage of low-income households in Los Angeles is higher than that of the subsample. Also, the percentage of employed people is higher

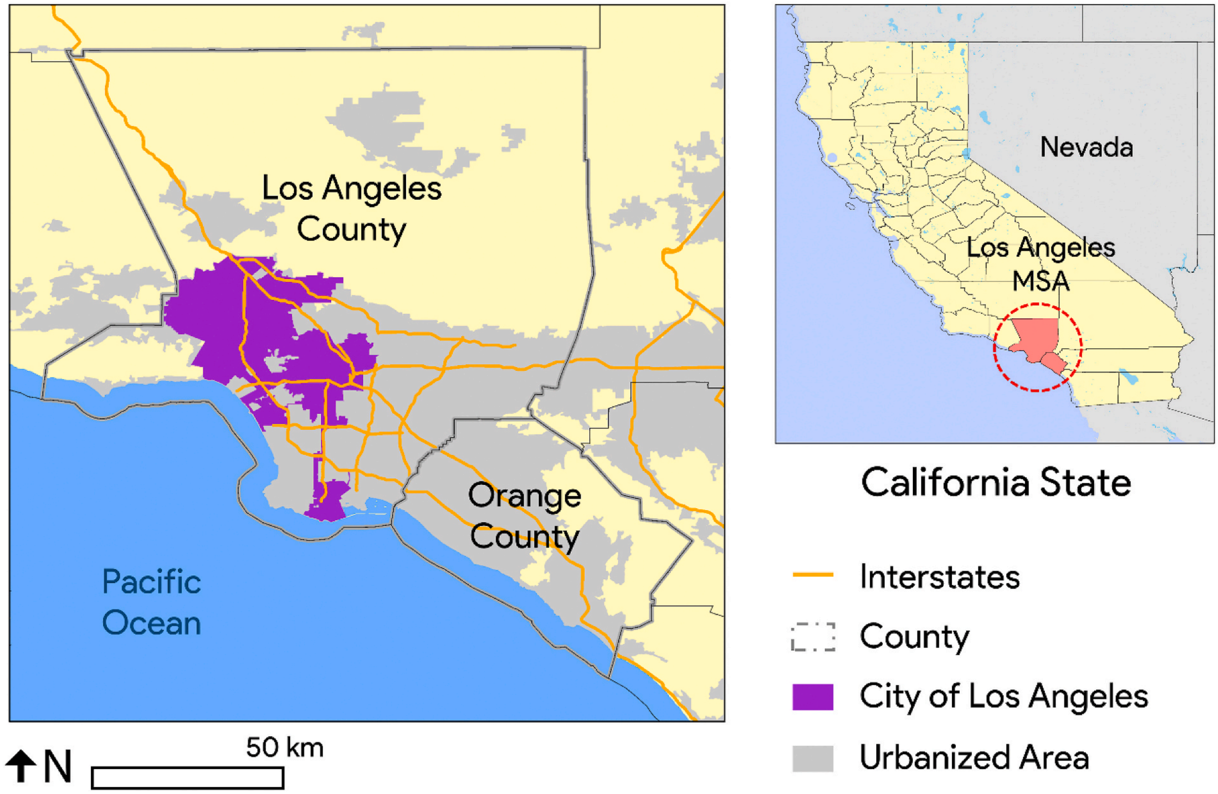

Fig. 2. The Los Angeles Metropolitan Statistical Area (MSA).

in the weekday subsample than the weekend subsample.

2.2.2. Data of ground-level ozone concentration, nitrogen oxides, and temperature

We use hourly (0–23h) ground-level ozone concentration and nitrogen oxides data from 26 monitoring stations and hourly temperature data from 81 monitoring stations located in and near the study area. We randomly select one weekday (Wednesday, August 15th) and one weekend day (Saturday, August 18th) in summer 2018. We focus on summer since relatively higher ground-level ozone concentrations are easily observed. These data are obtained from the California Air Resources Board (CARB) online database.

We choose ground-level ozone as the air pollutant to study because ground-level ozone, which is one of the six criteria pollutants for National Ambient Air Quality Standards (NAAQS) designated by the U.S. Environmental Protection Agency (EPA), is especially vital for respiratory health. Previous studies have actively investigated the negative effects of ground-level ozone exposure on people's health outcomes (e.g., Jerret et al., 2009; Levy et al., 2005). It is widely known that even relatively low ozone levels can cause critical damage to people's lungs and airways (Environmental Protection Agency, 2020).

Note that, although there is a temporal mismatch between the air pollution data (2018) and the activity-travel data (2017), we can still use these data for the purpose of methodological investigation because ozone levels and human daily mobility patterns are unlikely to be drastically different over one year (because the driving factors change slowly over time; e.g., people's activity-travel patterns reflect their routine daily mobility patterns, which do not change considerably over one year). Therefore, the slight temporal mismatch is unlikely to significantly affect the conclusion of this study.

Table 1
Comparison of the sociodemographic variables of the weekday/weekend subsample with those of the Los Angeles MSA.

Variables		Weekday Participants [a]	Weekend Participants [b]	Los Angeles MSA [c]
Female %		51.8%	52.5%	51.0%
Race	White [d] %	54.9%	52.0%	54.0%
	Black %	5.5%	5.8%	7.0%
	Asian %	16.2%	16.7%	16.0%
Mean age (years old)		50.5	51.0	45.0
Employed people %		61.1%	54.7%	60.0%
Low-income household [e] %		5.7%	7.0%	9.7%

Notes: [a] n = 2640 [b] n = 1150 [c] American Community Survey (ACS) 2017 5-year estimates (16+ years old) [d] Non-Hispanic White [e] Household income less than $15,000 per year.

2.3. Methods

2.3.1. Measuring residence-based and mobility-based individual exposures

First, we create 24 hourly (0–23h) ground-level ozone concentration surfaces at a 1 square km resolution by utilizing co-kriging estimation. Different sets of ground-level ozone surfaces are estimated for one weekday (August 15, 2018) and one weekend day (August 18, 2018). Although it would be ideal to create more spatiotemporally detailed surfaces, because of limitations in data and computing resources, we assume that air pollution levels are constant within an hour interval and a 1 square km grid. The co-kriging estimation uses a primary variable (i.e., ground-level ozone) and secondary variables (i.e., nitrogen oxides and temperature), which are strongly correlated to the primary variable (Singh et al., 2011; Park and Kwan, 2017; Phillips et al., 1997). Co-kriging estimation is chosen over other methods, including dispersion models and land-use regression, because co-kriging is more flexible for creating an hourly estimated surface in consideration of data limitations and computing resources (Berman et al., 2015; Jerrett et al., 2005b). Different variograms and model parameters are tested for choosing the best fit model based on the cross-validated R-square values and Root Mean Square Errors (RMSE). As a result, for the weekday ozone surface model, we use the Gaussian variogram as it has a higher cross-validated R-square (0.87) and a lower RMSE than other models. For the weekend model, we use the exponential variogram that yields a cross-validated R^2 of 0.68. Fig. 3 presents the estimated ground-level ozone concentration surfaces of selected hours of the weekday and the weekend day. Overall, the figure shows that (1) ozone levels are higher in afternoon times than in the morning and night times, and (2) ozone levels of inland areas are higher than shoreline areas. These patterns are in line with the results of previous studies that estimate the ozone concentration surfaces of Los Angeles (e.g., California Environmental Protection Agency 2014; Park and Kwan, 2017).

Next, we estimate each participant's daily exposure to ground-level ozone based on the two approaches: the residence-based approach and the mobility-based approach. Equation (1) measures E_i^R, which is a person i's residence-based ground-level ozone exposure:

$$E_i^R = \sum_{t=1}^{1,440} C(x_H, y_H, t) \tag{1}$$

where t denotes the time of a day (1-min interval), C is an hourly ground-level ozone concentration level obtained from co-kriging estimation, and (x_H, y_H) denotes a person i's home location reported in the survey. Equation (2) measures E_i^M, which is a person i's mobility-based ground-level ozone exposure:

$$E_i^M = \sum_{t=1}^{1,440} C(x_t, y_t, t) \tag{2}$$

where (x_t, y_t) denotes a person i's location at time t, which can be identified based on the individual's space-time path, which is constructed by a series of 3-dimensional points: longitude, latitude, and time (1-min interval). Although the air pollution surface is estimated every 1 h, the space-time path is generated with a 1-min interval since people can travel long distances within 1 h and thus are exposed to significantly different air pollution levels while traveling. An individual's space-time path is constructed based on information on the location and time of his/her activities reported in the activity-travel diary by using a time-geographic framework (Hägerstrand, 1970; Kwan, 1998, 2004; Miller, 1999). Travel routes of the space-time path are constructed based on the assumption that the participant used the shortest travel time paths between activity locations. Note that since the activity-travel survey did not collect actual GPS trajectories of each participant, the exact routes traveled by participants are unknown. Thus, we utilize the Google Maps API to estimate the most realistic routes based on the detailed real-world transport network and traffic congestion conditions of the study area (Kim and Lee, 2019; Kim and Kwan, 2019; Park, 2020).

In the end, we have two daily ground-level ozone exposure estimates (i.e., the residence-based and the mobility-based individual exposures) for each participant in our weekday and weekend subsample. Statistical analyses are conducted to see whether there is a significant difference between residence-based and mobility-based individual exposures, which is one of the important features of the NEAP (Kwan, 2018b). Besides, we observe whether the probability density function (PDF) of mobility-based individual exposures is less deviated than that of residence-based individual exposures, which indicates the presence of neighborhood effect averaging. To further examine the patterns of neighborhood effect averaging, we construct a scatter plot that has x-axis values as the residence-based individual exposures (E_i^R) and y-axis values obtained by subtracting the mobility-based from the residence-based individual exposures ($E_i^R - E_i^M$). Since neighborhood effect averaging indicates that high residence-based individual exposures become lower and low residence-based individual exposures become higher when people's daily mobility is considered, a positive linear relationship between x-axis values and y-axis values indicates the existence of neighborhood effect averaging (Kim and Kwan, 2021; Kwan, 2018b; Ma et al., 2020b; Tan et al., 2020).

2.3.2. *Examining the sociodemographic disparities in people's air pollution exposures*

This subsection describes how we address the first research question: How does the NEAP affect the evaluation of sociodemographic dispar-

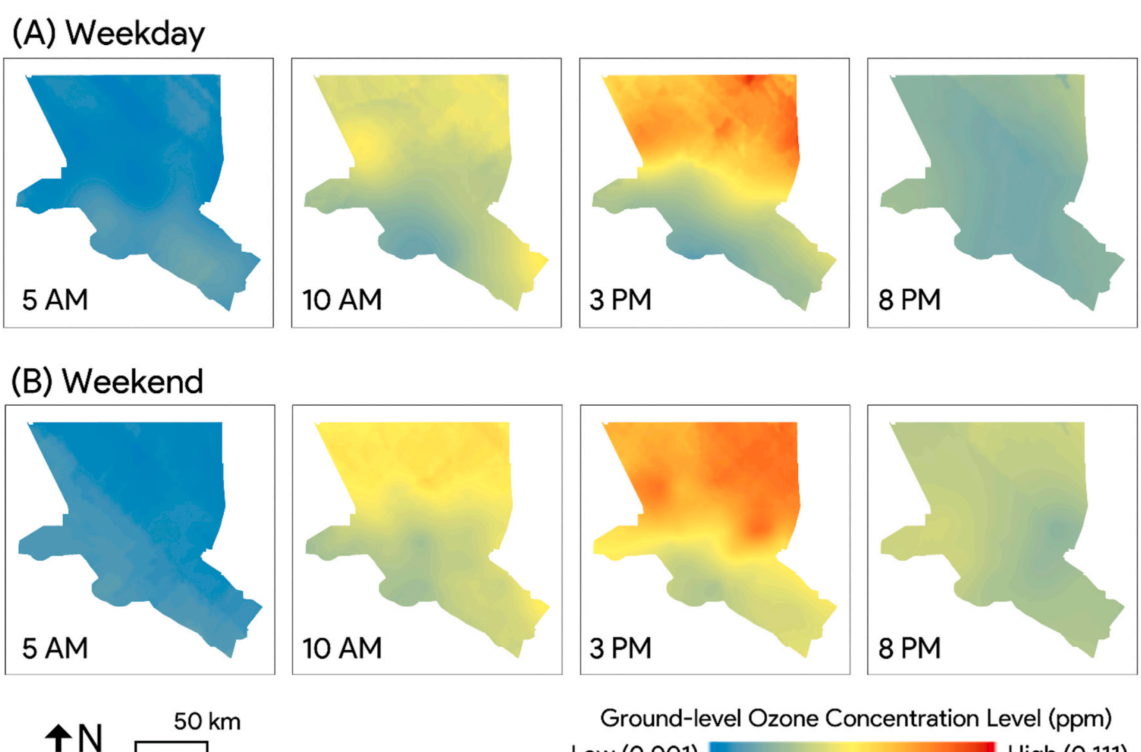

Fig. 3. Estimated hourly ground-level ozone concentration surfaces of (A) one weekday and (B) one weekend day (selected hours).

ities in people's air pollution exposures? For each participant group (i.e., weekday and weekend), we conduct two regression analyses to examine the association between individual exposure levels and sociodemographic characteristics. First, we focus on the weekday participants (Models 1 and 2). The dependent variable of Model 1 is residence-based individual exposure levels (E_i^R), and that of Model 2 is mobility-based individual exposure levels (E_i^M). The independent variables of each model include participants' age, race/ethnicity, gender, income level, employment status, and immigrant status. We choose a spatial regression model because of the existence of spatial autocorrelation in the residuals of the ordinary least squares (OLS) models. Specifically, the result of Lagrange multiplier tests of the OLS models suggests spatial error models (Anselin, 1988). For example, Model 1 is represented by Equation (3):

$$E_i^R = \beta_0 + \beta_1 Age_i + \beta_2 Female_i + \beta_3 Black_i + \beta_4 Asian_i + \beta_5 Others_i + \beta_6 Hispanic_i + \beta_7 Immigrant_i + \beta_8 LowIncome_i + \beta_9 HighIncome_i + \beta_{10} Employed_i + \lambda W \varepsilon_i + u_i \quad (3)$$

where λ is the spatial lambda, ε_i is the spatial component of the error term, and W is the spatial weight matrix (K-10 nearest neighbors). Among other types of spatial weight matrices (e.g., contiguity matrix type), the K-nearest neighbor type is selected because individual observations in the models are point-type data. Moreover, we investigate the sensitivity of the model results with different spatial weight matrices. We test four different numbers of neighbors (5, 7, 11, and 15), and the results are nearly the same.

By comparing the results of Model 1 with those of Model 2, we examine how the sociodemographic disparities in people's air pollution exposures are inaccurately evaluated when human daily mobility is overlooked. Specifically, we compare the direction, size, and statistical significance of the coefficients estimated in Model 2 with those estimated in Model 1. Different spatial regression models are estimated for participants who reported weekday trips (n = 2640; Models 1 and 2) and who reported weekend trips (n = 1150; Models 3 and 4). Table 2 presents the descriptive statistics of the independent variables included in Models 1–4.

2.3.3. *Identifying the sociodemographic characteristics of the doubly disadvantaged in air pollution exposures*

This subsection describes how we answer the second research question: Which social groups with high residence-based exposures do not experience neighborhood effect averaging? In other words, who are doubly disadvantaged in air pollution exposures? We first define the doubly disadvantaged group. Recall that the NEAP suggests that most people who reside in high-pollution neighborhoods (i.e., high residence-based exposure levels) can experience *downward averaging*. As a result, their mobility-based exposure levels can be lower than their residence-based exposure levels. However, the doubly disadvantaged group consists of people (1) whose residence-based exposure level is relatively high (among the study participants) and (2) whose mobility-based exposure level is higher than the residence-based exposure level (Equation (4)).

$$DD_i = \begin{cases} 1 & \text{if } Z(E_i^R) \geq 0.5 \text{ and } E_i^M > E_i^R \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where DD_i denotes whether individual i is doubly disadvantaged (=1; otherwise = 0). Next, to identify the sociodemographic characteristics of

Table 2
Descriptive statistics of the independent variables included in the spatial regression model.

Variables		Description	Models 1–2 [a]	Models 3–4 [b]
Age		Age	50.5 (17.1) [c]	51.0 (17.4)
Female %		1 = female; 0 = otherwise	51.8%	52.5%
Race	Black %	1 = Black; 0 = White	5.5%	5.8%
	Asian %	1 = Asian; 0 = White	16.2%	16.7%
	Others %	1 = Others; 0 = White	11.3%	14.1%
Hispanic/Latino %		1 = Hispanic/Latino; 0 = otherwise	19.5%	20.3%
Immigrant %		1 = immigrant; 0 = nonimmigrant	28.3%	29.3%
Income level [d]	Low %	1 = low-income; 0 = middle-income	5.7%	7.0%
	High %	1 = high-income; 0 = middle-income	14.1%	12.2%
Employed people %		1 = employed; 0 = otherwise [e]	61.1%	54.7%

Notes: [a] n = 2640 [b] n = 1150 [c] mean and standard deviation [d] Low-income: household income less than $15,000 per year; High-income: household income higher than $200,000 per year. [e] Otherwise: the unemployed, homemakers, students, and the retired.

Table 3
Descriptive statistics of residence-based and mobility-based individual exposures of weekday and weekend participants.

		Mean (ppm)	Standard Deviation
Weekday (n = 2640)	Residence-based individual exposures	33.921	6.010
	Mobility-based individual exposures	33.500	5.664
	Differences	0.421***[a]	–
Weekend (n = 1150)	Residence-based individual exposures	46.338	4.804
	Mobility-based individual exposures	46.246	4.630
	Differences	0.092[a]	–

Notes: *** denotes $p < 0.001$; [a] Paired sample *t*-test.

the doubly disadvantaged people while accounting for spatial autocorrelation, a spatial autologistic regression model is used. The spatial autologistic regression model focuses on participants whose residence-based exposure levels are high (i.e., $Z(E_i^R) \geq 0.5$), which is a characteristic of the doubly disadvantaged group.

3. Results

3.1. Results of measuring residence-based and mobility-based individual exposures

Table 3 presents the descriptive statistics of residence-based and mobility-based individual exposures of the weekday and weekend participants. In the weekday, the pairwise differences between residence-based and mobility-based individual exposures are significant, which is in line with the results of previous studies (e.g., Dewulf et al., 2016; Guo et al., 2020; Nyhan et al., 2019; Setton et al., 2011; Shafran-Nathan et al., 2017; Park and Kwan, 2017; Yu et al., 2018; Yu et al., 2020). The standard deviation of mobility-based individual exposures is smaller than that of residence-based individual exposures, indicating the presence of neighborhood effect averaging in people's exposure to air pollution (Dewulf et al., 2016; Kim and Kwan, 2021; Kwan, 2018b; Ma et al., 2020b; Yu et al., 2018). Furthermore, Fig. 4(A) shows that the probability density function (PDF) of mobility-based individual exposures is less deviated than that of residence-based individual exposures, indicating that individual exposures tend to converge toward the average exposure level of the participants. Besides, Fig. 5(A) shows that there is a positive linear relationship between residence-based individual exposures (i.e., x-axis values) and values obtained by subtracting the mobility-based from the residence-based individual exposures (i.e., y-axis values). The results in Figs. 4(A) and 5(A) provide strong evidence for the presence of neighborhood effect averaging in people's air pollution exposures of the weekday.

In the weekend, however, the pairwise differences between residence-based and mobility-based individual exposures are not significant. Therefore, the result indicates that neighborhood effect averaging is weak or absent in people's air pollution exposures for the weekend. Fig. 4(B) also indicates that the PDF of residence-based individual exposures and that of mobility-based individual exposures are nearly the same. Besides, Fig. 5(B) reveals that there is a weak positive linear relationship between x-axis and y-axis values, indicating a weak manifestation of neighborhood effect averaging. When comparing between the weekday and weekend exposures, the average residence-based and mobility-based individual exposures are higher in the weekend than the weekday. This indicates the *ozone weekend effect*, which is a phenomenon observed in urban areas that ground-level ozone concentration levels are typically higher in the weekend than the weekday despite the low nitrogen oxides emission from vehicles (Gao and Niemeier, 2007; Yarwood et al., 2003).

3.2. Results of the spatial regression models

In this subsection, we investigate the NEAP in the evaluation of sociodemographic disparities in people's air pollution exposure (RQ1). Table 4 illustrates the results of the spatial regression models on the association between individual exposures and sociodemographic characteristics of weekday and weekend participants.

3.2.1. Weekday models (models 1 and 2)

The results of Model 1 reveal that Black and low-income people tend to have significantly lower residence-based individual exposures when compared to the other groups (i.e., white and middle-income people), which is in line with the results of previous studies that focused on people's residential ozone exposures (e.g., Hajat et al., 2015; Liu, 1996; Yu and Stuart, 2016). Also, the results of Model 2 indicate that the mobility-based exposure of employed people (workers) is significantly lower than that of non-workers.

Next, we compare the results of Model 2 with those of Model 1. First, although Black and low-income people tend to have lower residence-based individual exposures than the other groups (Model 1), being Black and low-income is not a significant factor affecting a person's mobility-based individual exposure (Model 2). This suggests that using residence-based exposure assessments can overestimate the disparity in exposures between Black and White people and low- and middle-income people. Second, employment status is significantly associated with mobility-based individual exposures (Model 2) but is not associated with residence-based individual exposures (Model 1). This means that using residence-based exposure assessments can underestimate the disparity

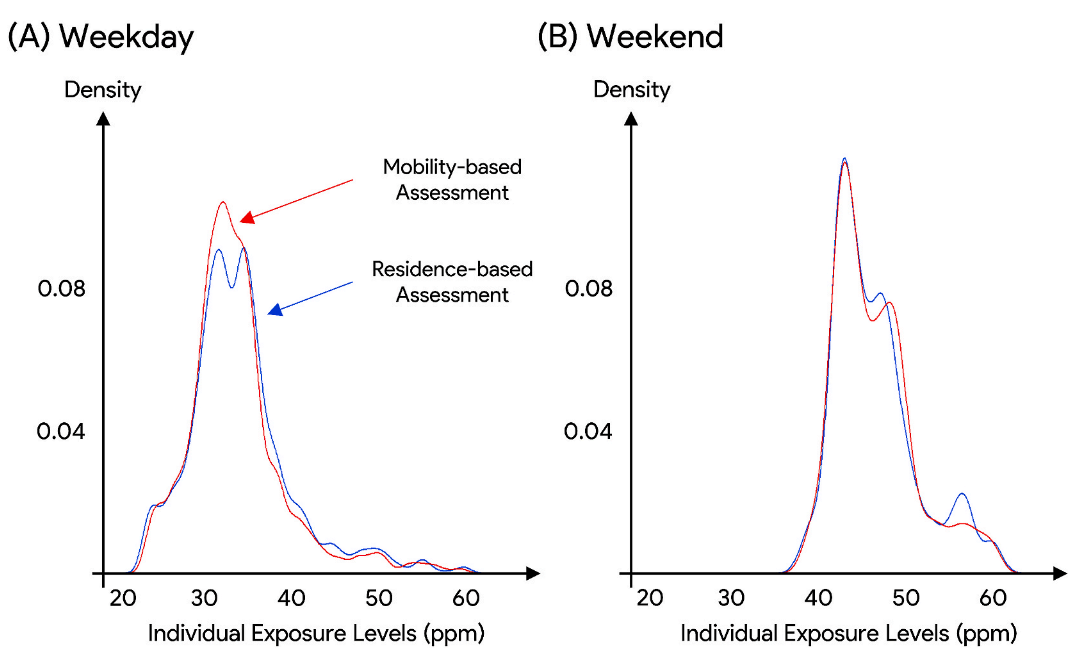

Fig. 4. Probability density functions (PDF) of residence-based (blue line) and mobility-based (red line) individual exposures of (A) weekday and (B) weekend participants. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

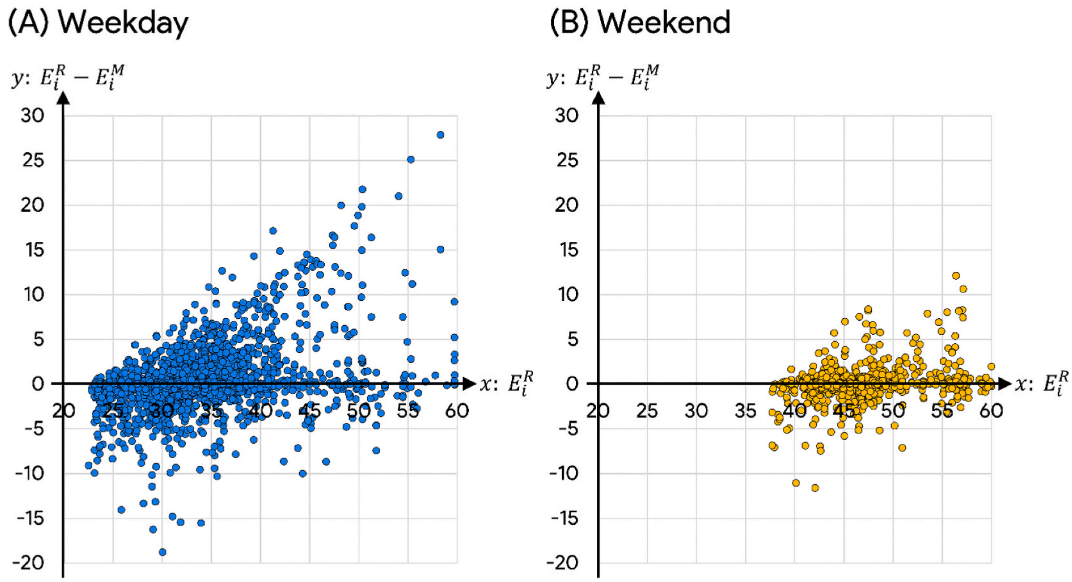

Fig. 5. A scatter plot having x-axis values as the residence-based individual exposures and y-axis values obtained by subtracting the mobility-based from the residence-based individual exposures of (A) weekday and (B) weekend participants.

Table 4
Results of the spatial regression models on the association between individual sociodemographic characteristics and residence-based and mobility-based individual exposures.

	Weekday Model 1 [(a)]	Model 2 [(b)]	Weekend Model 3 [(a)]	Model 4 [(b)]
Age	0.005	0.004	0.001	0.002
	(0.004)	(0.003)	(0.001)	(0.003)
Female	−0.108	0.104	−0.025	0.013
	(0.128)	(0.084)	(0.025)	(0.105)
Black	−1.044***	−0.169	0.060	0.377
	(0.310)	(0.204)	(0.069)	(0.282)
Asian	0.003	0.016	0.024	−0.259
	(0.217)	(0.143)	(0.044)	(0.180)
Others	−0.269	0.116	0.009	−0.251
	(0.225)	(0.148)	(0.043)	(0.176)
Hispanic	0.160	−0.102	0.014	0.054
	(0.192)	(0.127)	(0.040)	(0.165)
Immigrant	0.123	−0.062	0.007	−0.007
	(0.168)	(0.110)	(0.033)	(0.136)
Low Income	−0.734*	−0.239	0.046	0.364
	(0.293)	(0.193)	(0.054)	(0.221)
High Income	−0.087	0.037	−0.081	0.306
	(0.190)	(0.125)	(0.044)	(0.179)
Employed	0.143	−0.250*	−0.026	−0.083
	(0.148)	(0.097)	(0.028)	(0.116)
λ	0.851***	0.918***	0.985***	0.908***
Intercept	33.523***	33.327***	47.725***	46.069***
	(0.531)	(0.566)	(0.898)	(0.637)
Log-Likelihood	−7130.456	−6090.001	−862.328	−2423.875
AIC	14286.910	12206.000	1750.656	4873.749
Observations	2640	2640	1150	1150

Notes: *** denotes $p < 0.001$, * denotes $p < 0.05$; Standard errors in parenthesis; [(a)] Dependent variable: Residence-based individual exposures; [(b)] Dependent variable: Mobility-based individual exposures.

in air pollution exposures between workers and non-workers.

We further explore how the NEAP manifests in the evaluation of sociodemographic disparities in people's ozone exposures while focusing on race (Black and White people), income (low- and middle-income people), and employment status (workers and non-workers). Specifically, we examine how each group is exposed to different levels of ozone in daytimes (e.g., 10 a.m. to 6 p.m.). The daytimes are when most people might undertake daily activities in out-of-home neighborhoods and thus their mobility-based exposures can be different from their residence-based exposures (Kim and Kwan, 2021; Ma et al., 2020a,b; Yu et al., 2020). For each sociodemographic group, Fig. 6 shows hourly average residence-based (represented by the dotted line) and mobility-based individual exposures (represented by the solid line), and Fig. 7 illustrates a scatter plot obtained using the same method used to create Fig. 5 in Section 3.1.

First, we examine how the NEAP operates for the disparity in exposures between Black and White people. Fig. 6(A) illustrates that, for White people, the hourly average mobility-based exposure (represented by the red solid line) is lower than the hourly average residence-based exposure (represented by the red dotted line). The paired sample *t*-test result also indicates that the difference in total ozone exposure levels in the daytime (10 a.m.-6 PM) is significant between the mobility-based and the residence-based assessments ($p < 0.001$). This indicates that White people experience *downward averaging* in their ozone exposures while undertaking daily activities. On the contrary, Fig. 6(A) shows that, for Black people, the hourly average mobility-based exposure (represented by the blue solid line) is similar to the hourly average residence-based exposure (represented by the blue dotted line). The paired sample *t*-test result also reveals that the difference between the mobility-based and the residence-based exposure levels during the daytime is not significant. This indicates that Black people do not experience neighborhood effect averaging. The scatter plot in Fig. 7(A) corroborates these findings. For observations of White people (represented by blue dots), there is a positive linear relationship between residence-based individual exposures (i.e., x-axis) and values obtained by subtracting the mobility-based from the residence-based individual exposures (i.e., y-axis), indicating the presence of neighborhood effect averaging. On the contrary, for observations of Black people (represented by orange triangles), there is a weak positive linear relationship between x-axis values and y-axis values, meaning that neighborhood effect averaging is weak or absent. To sum up, although the average residence-based ozone exposure of White people is higher than that of Black people, the difference in exposure between these two groups becomes insignificant when people's daily mobility is considered. This is because White people experience *downward averaging* in their ozone exposures, while Black people do not.

Second, we investigate how the NEAP operates for the disparity in exposures between low- and middle-income people. Fig. 6(B) shows that, for middle-income people, the hourly average mobility-based

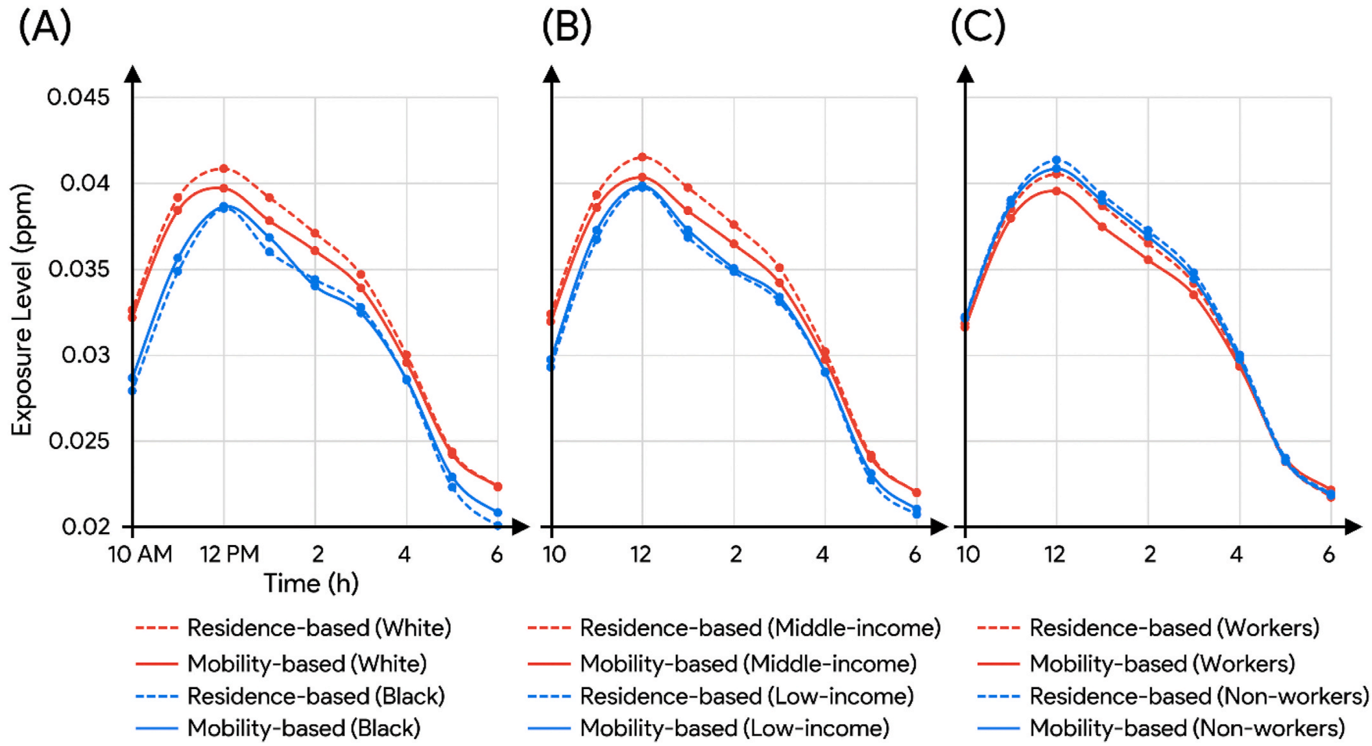

Fig. 6. Hourly average residence-based (represented by the dotted line) and mobility-based individual exposures (represented by the solid line) of each socio-demographic group: (A) Black and White people; (B) Low- and Middle-income people; (C) Non-workers and Workers.

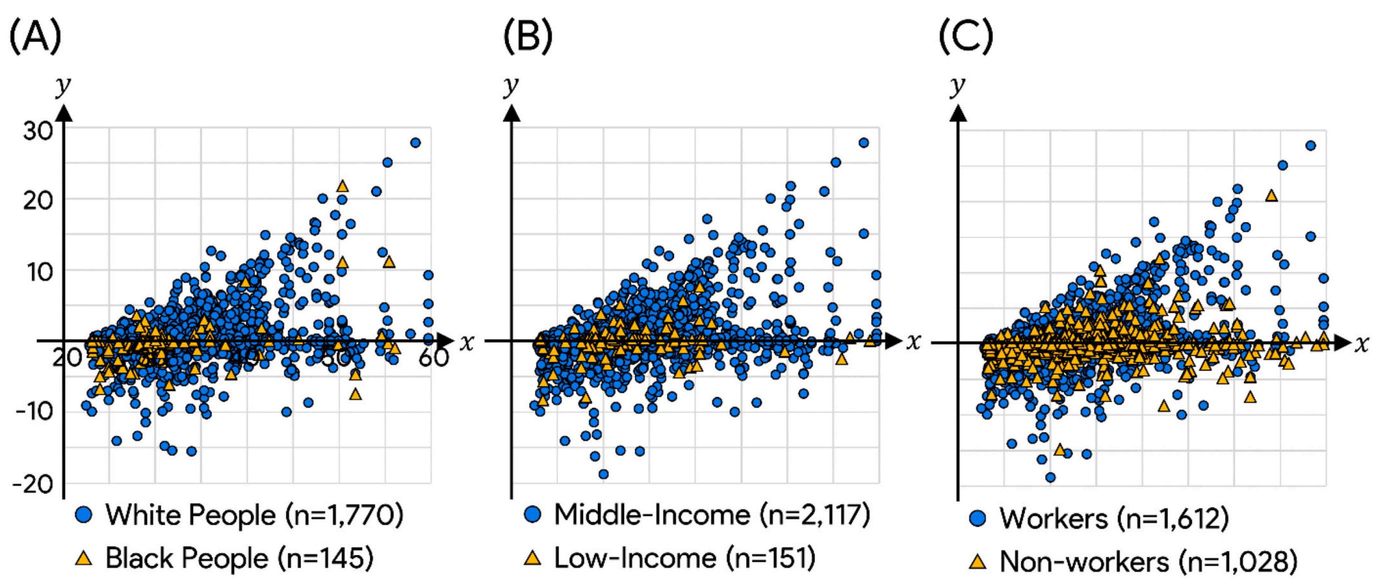

Fig. 7. A scatter plot having x-axis values (E_i^R) as the residence-based individual exposures and y-axis values ($E_i^R - E_i^M$) obtained by subtracting the mobility-based from the residence-based individual exposures of (A) Black and White participants, (B) Low- and Middle-income participants, and (C) Non-workers and Workers.

exposure (represented by the red solid line) is lower than the hourly average residence-based exposure (represented by the red dotted line). The paired sample *t*-test result also indicates that the difference in total ozone exposure levels in the daytime is significant between the mobility-based and the residence-based assessments ($p < 0.001$). This indicates that middle-income people experience *downward averaging* in their exposures while undertaking daily activities. However, Fig. 6(B) illustrates that, for low-income people, the hourly average mobility-based exposure (represented by the blue solid line) is similar to the hourly average residence-based exposure (represented by the blue dotted line). The paired sample *t*-test result also reveals that the difference between the mobility-based and the residence-based exposure levels during daytime is not significant. This means that low-income people do not experience neighborhood effect averaging. The scatter plot in Fig. 7(B) corroborates these findings and shows that there is a stronger positive linear relationship for middle-income people than low-income people. In sum, although the average residence-based ozone exposure of middle-income people is higher than that of low-income people, the difference becomes insignificant when people's daily mobility is considered. This is because middle-income people experience *downward averaging* in their ozone exposures, while low-income people do not.

Lastly, we examine how the NEAP operates for the disparity in exposures between workers and non-workers. Fig. 6(C) illustrates that, for workers, the hourly average mobility-based exposure (represented by the red solid line) is lower than the hourly average residence-based exposure (represented by the red dotted line). The paired sample *t*-test result also indicates that the difference in total ozone exposure levels in the daytime is significant between the mobility-based and the residence-based assessments ($p < 0.001$). This indicates that workers experience *downward averaging* in their exposures while undertaking daily activities. On the contrary, Fig. 6(C) shows that, for non-workers, the hourly average mobility-based exposure (represented by the blue solid line) is similar to the hourly average residence-base exposure (represented by the blue dotted line). The paired sample *t*-test result also reveals that the difference between the mobility-based and the residence-based exposure levels during daytime is not significant. This suggests that non-workers do not experience neighborhood effect averaging. The scatter plot in Fig. 7(C), which corroborates these findings, shows that there is a stronger positive linear relationship for workers than non-workers. In summary, although there is no significant difference in average residence-based ozone exposure between workers and non-workers, the average mobility-based ozone exposure of workers is significantly lower than that of non-workers. This is because workers experience *downward averaging* in their ozone exposures, while non-workers do not.

To sum up, the results indicate that the difference in average residence-based air pollution exposure between two sociodemographic groups can be overestimated or underestimated when human daily mobility is ignored. This is because of the different manifestations of neighborhood effect averaging of each group (Kim and Kwan, 2021; Kwan, 2018b; Ma et al., 2020b). The results suggest that, when examining the sociodemographic disparities in air pollution exposures, ignoring human daily mobility can exacerbate the neighborhood effect averaging problem (NEAP). In this light, public health policymakers should pay more attention to human daily mobility to take the NEAP into account when evaluating sociodemographic disparities in exposures (Kestens et al., 2017; Kim and Kwan, 2021; Kwan, 2018b; Shareck et al., 2014).

3.2.2. Weekend models (models 3 and 4)

Focusing on the weekend participants, the results of Model 3 indicate that there is no significant association between sociodemographic characteristics and residence-based individual exposures. The results of Model 4 (the mobility-based individual exposures) also illustrate that there is no significant association. One of the reasons for having the same result is that there is no significant difference between residence-based and mobility-based individual exposures for weekend participants (See Table 3 in Section 3.1). In our study, the difference between residence-based and mobility-based individual exposures is not significant in the weekend because of the smaller regional variation in ozone concentrations and participants' lower level of daily mobility in the weekend when compared to the weekday.

First, the standard deviation of residence-based individual exposures of weekend participants (4.804) is smaller than that of weekday participants (6.010), indicating that the regional variation of ozone concentrations of the weekend is smaller than that of the weekday (See Table 3 in Section 3.1). Since there is no significant difference in ozone concentration levels over space, even if people travel to out-of-home neighborhoods to undertake daily activities, their mobility-based exposures can be similar to their residence-based exposures.

Second, the level of daily mobility is lower in the weekend than weekday participants. If people have a lower level of daily mobility (i.e., people spend most of their time in their residential neighborhoods), their mobility-based ozone exposures can be similar to their residence-based exposures. Following an approach in previous studies that measure the level of people's daily mobility (Setton et al., 2011; Shafran-Nathan et al., 2017; Yoo et al., 2015), Table 5 compares key daily mobility indices of weekday participants with those of weekend participants. The unpaired two-sample *t*-test results illustrate that the average duration of out-of-home activities of weekend participants is significantly lower than that of weekday participants. The results indicate that the level of participants' daily mobility is lower in the weekend than in the weekday, which corroborates findings from previous studies (Federal Highway Administration, 2018; Zhong et al., 2008).

Therefore, the results suggest that neighborhood effect averaging in the evaluation of sociodemographic disparities in people's air pollution exposure is weak or absent when there is a small variation in ozone concentrations over space or when people have lower levels of daily mobility. However, one caveat is that these results cannot be generalized to a direct comparison between weekday and weekend because the results are based on cross-sectional data (i.e., one randomly selected day). For example, it is unclear that less variation in ozone concentrations in the weekend than the weekday can still be observed in other study areas and other seasons of the year.

3.3. Doubly disadvantaged people in air pollution exposure

In this subsection, we identify the sociodemographic characteristics of people who are doubly disadvantaged in outdoor ground-level ozone exposures (RQ2). Recall that the doubly disadvantaged group consists of people whose residence-based exposure levels are relatively high among a population but do not experience neighborhood effect averaging (especially, *downward averaging*). Since our weekend data do not manifest the neighborhood effect averaging problem (NEAP), we focus on the weekday participants. Among 2640 participants in the weekday

Table 5
Comparison of the key daily mobility indices of the weekday observations with those of the weekend observations.

	Weekday (Mean)	Weekend (Mean)	p-value[1)]
The number of daily trips	4.164	4.228	0.427
Average distance of out-of-home activity locations from home (km)	6.158	6.366	0.527
Duration of out-of-home activities (min)	354	245	0.000

Notes: [1)] Unpaired two-sample *t*-test results.

Table 6
Results of the spatial autologistic regression model on the association between individual sociodemographic characteristics and the odds of being doubly disadvantaged in ozone exposures.

	Model 5
Age	−0.007 (0.006)
Female	0.063 (0.194)
Black	1.038 (0.542)
Asian	0.361 (0.317)
Others	0.032 (0.312)
Hispanic	0.238 (0.249)
Immigrant	0.169 (0.244)
Low Income	0.344 (0.414)
High Income	0.277 (0.316)
Employed	−0.660** (0.203)
Autocovariate	3.087*** (0.449)
Intercept	−1.393** (0.440)
Log-Likelihood	−323.633
AIC	671.267
Observations	560

Notes: *** denotes $p < 0.001$, ** denotes $p < 0.01$; Standard errors in parenthesis.

subsample, 560 participants have a relatively high residence-based exposure level (top 20%). Among these 560 participants, 194 (35%) are doubly disadvantaged according to the abovementioned criteria. Table 6 illustrates the results of a spatial autologistic regression model (Model 5). The results indicate that, for those who live in high air pollution neighborhoods, non-workers (e.g., unemployed, homemakers, retired, and students) have significantly higher odds of being doubly disadvantaged (i.e., lower odds of experiencing *downward averaging*) in ozone exposures than workers.

Based on recent studies on the NEAP, the doubly disadvantaged people in air pollution exposures have distinctive characteristics. The first is that they tend to spend most of their time in their residential neighborhoods as the spatial entrapment hypothesis suggests (Kwan, 1999; McLafferty and Preston, 1996). In other words, they have a very low level of daily mobility. The second characteristic is that these people are exposed to high air pollution levels while undertaking daily activities in out-of-home neighborhoods (as observed in Ma et al., 2020b). In our study, we observed that most doubly disadvantaged people belong to the first case. For example, their average number of daily trips is 3.902, the average of mean distance of out-of-home activity locations from home is 4.752 km, and the mean duration of out-of-home activities is 275 min. These mobility indices are significantly lower ($p<0.01$) than those of the other weekday participants except for the average number of daily trips.

The results imply that public health policies should pay special attention to the doubly disadvantaged group to fully mitigate sociodemographic disparities in people's air pollution exposures. This is because doubly disadvantaged people have limited daily mobility and do not experience *downward averaging*, which is experienced by most other people living in high-pollution neighborhoods. This finding may reflect that the doubly disadvantaged groups might have been marginalized in the decision-making process related to local land use and transportation system planning, which may result in their low level of daily mobility (Golledge and Stimson 1997; Osypuk and Acevedo-Garcia, 2010; Shareck et al., 2014). Thus, public health policies can focus on enhancing the daily mobility of the doubly disadvantaged group by providing these people with environmentally friendly mobility options so that they can also experience *downward averaging* (Kwan, 2018b; Nieuwenhuijsen and Khreis, 2018).

4. Conclusion

The neighborhood effect averaging problem (NEAP) is a major methodological problem that might affect the accuracy of assessments of individual exposure to mobility-dependent environmental factors (e.g., air/noise pollution, green/blue spaces, or healthy food environments). This research examined the NEAP in the evaluation of sociodemographic disparities in people's exposure to outdoor ground-level ozone as a major air pollutant. We utilized geographic information science methods to estimate hourly (0–23h) ground-level ozone concentration surfaces and a one-day activity-travel diary dataset collected in Los Angeles. We measured participants' residence-based and mobility-based individual exposures and estimated spatial regression models to assess the relationships between individual sociodemographic characteristics and exposure levels. Lastly, we examined the sociodemographic characteristics of people who are doubly disadvantaged in air pollution exposures (i.e., who live in high pollution neighborhoods but cannot experience *downward averaging*) using a spatial autologistic regression model.

We investigated how the NEAP affects the evaluation of sociodemographic disparities in people's outdoor ground-level ozone exposures (RQ1). The results of the spatial regression models revealed that the difference in average residence-based air pollution exposure between two social/racial groups can be inaccurately assessed when people's daily mobility is ignored because of the different manifestations of neighborhood effect averaging for each group. Therefore, we concluded that ignoring human daily mobility can aggravate the NEAP in the evaluation of sociodemographic disparities in air pollution exposures. By comparing the results obtained from weekday participants with those obtained from weekend participants, we illustrated that the NEAP was weak or not present when there is a small variation in ozone concentrations over space and people have low levels of daily mobility. Next, we examined the sociodemographic characteristics of people who are doubly disadvantaged in outdoor ground-level ozone exposures (RQ2). The results of the spatial autologistic regression model revealed that non-workers (e.g., unemployed, homemakers, retired, and students) have significantly higher odds of being doubly disadvantaged in outdoor ground-level ozone exposures than workers.

This study is significant as it is one of the first studies that systematically investigate the NEAP in the evaluation of sociodemographic disparities in people's outdoor ground-level ozone exposure. Specifically, considering that the inaccurate evaluation of sociodemographic disparities in people's air pollution exposures can lead to erroneous results in environmental inequality research and ineffective public policy formulations, our results strongly suggest that researchers and policymakers should consider human daily mobility to take the NEAP into account.

Moreover, although we focused on outdoor ground-level ozone exposures, the results suggest that the NEAP may be present when studying other mobility-dependent air pollutants, such as particulate matter and nitrogen oxides. For example, previous studies have concluded that the residence-based $PM_{2.5}$ exposure of low-income people is significantly higher than that of high-income people (e.g., Hajat et al., 2015). However, our results suggest that high-income people may experience neighborhood effect averaging (in this case, *upward averaging*), while low-income people may not experience it. Thus, the difference in the average $PM_{2.5}$ exposure between low- and high-income people may become smaller when human daily mobility is considered. Further, considering that low-income people typically have lower levels of daily mobility, these people are likely to be doubly disadvantaged in their $PM_{2.5}$ exposure. In this light, it would be critical for future studies to examine how the NEAP operates in the evaluation of sociodemographic disparities in exposures to various air pollutants.

However, there are several limitations to our study that should be addressed in future research. First, due to the limitations in data and computing resources, our ground-level ozone concentration surfaces assumed that the concentration level is constant within an hour and a 1-square km grid, which might not be able to capture detailed spatio-temporal variations in ground-level ozone concentrations. Besides, due to data limitation, we assumed that indoor ozone level is the same as outdoor ground-level ozone. Considering that some people (e.g., office workers) spend most of their daytime indoor and indoor ozone levels can be high in certain settings (e.g., near photocopying machines), this assumption may introduce uncertainties to individual ozone exposure estimations (Allen et al., 1978). Thus, future studies should model air pollution with higher resolutions and consider various microenvironments (indoor/outdoor) to examine the NEAP in the evaluation of sociodemographic disparities in people's air pollution exposures.

Second, since our study utilized data of one weekday and weekend day in the summer season (i.e., cross-sectional data), it remains unclear whether the NEAP still operates when other days in other seasons are selected. This is because ground-level ozone concentrations and people's daily mobility patterns may vary across seasons and over time (e.g., Bogaert et al., 2009; Susilo and Kitamura, 2005). Therefore, future studies should examine the NEAP by using data that are obtained from multiple times. Third, we focused only on ground-level ozone, which may not be sufficient for a comprehensive assessment of air pollution exposures because other important mobility-dependent air pollutants negatively affect people's health, such as particulate matter (PM) and carbon monoxide (CO). Therefore, future research should consider various mobility-dependent air pollutants when investigating the NEAP.

Credit author statement

Junghwan Kim, Contributed to the conceptualization, Methodology, Formal analysis, Investigation, Writing (original draft), Writing (revisions) of the paper. Mei-Po Kwan, Contributed to funding acquisition and the conceptualization, Writing (original draft), Writing (revisions) of the paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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