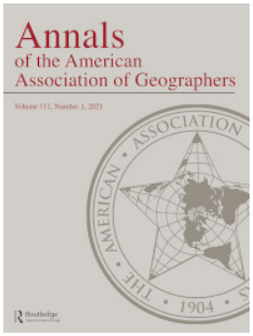

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How Neighborhood Effect Averaging Might Affect Assessment of Individual Exposures to Air Pollution: A Study of Ozone Exposures in Los Angeles

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The neighborhood effect averaging problem (NEAP) can be a serious methodological problem that leads to erroneous assessments when studying mobility-dependent exposures (e.g., air or noise pollution) because people's daily mobility could amplify or attenuate the exposures they experienced in their residential neighborhoods. Specifically, the NEAP suggests that individuals' mobility-based exposures tend toward the mean level of the participants or population of a study area when compared to their residence-based exposures. This research provides an in-depth examination of the NEAP and how the NEAP is associated with people's daily mobility through an assessment of individual exposures to ground-level ozone using the activity-travel diary data of 2,737 individuals collected in the Los Angeles metropolitan statistical area. The results obtained with exploratory analysis (e.g., a scatterplot and histograms) and spatial regression models indicate that the NEAP exists when assessing individual exposures to ozone in the study area. Further, high-income, employed, younger, and male participants (when compared to low-income, nonworking, older, and female participants) are associated with higher levels of neighborhood effect averaging because of their higher levels of daily mobility. Finally, three-dimensional interactive geovisualizations of the space-time paths and hourly ozone exposures of seventy-one selected participants who live in the same neighborhood corroborate the findings obtained from the spatial regression analysis. *Key Words: air pollution, human mobility, neighborhood effect, neighborhood effect averaging problem (NEAP), uncertain geographic context problem (UGCoP).*

For decades, the neighborhood effect has been an important notion in many disciplines, including geography, environmental health, sociology, and political science. It is the concept that people's behaviors or conditions (e.g., health outcomes) are affected by the physical and social environments of their residential neighborhoods (e.g., Wilson 1987; Sampson, Raudenbush, and Earls 1997; Diez Roux 2001; Macintyre and Ellaway 2003; Leal and Chaix 2011; van Ham et al. 2012; Arcaya et al. 2016; Clary, Matthews, and Kestens 2017). Past studies on the neighborhood effect have advanced our understanding of the relationships between neighborhood environments and a wide range of social phenomena, such as crime, substance use, and low birth weight, in important ways.

When delineating the neighborhood context, however, most studies to date have adopted a residence-based approach by using the residential neighborhood as the contextual area (Frumkin 2006; Inagami, Cohen, and Finch 2007; Matthews 2008; Kwan 2012, 2018a). They assumed that people's exposures to environmental influences can be adequately captured using their residential neighborhoods, which were often delineated as fixed administrative areas like census tracts or census blocks. These studies thus assumed that a person's residential neighborhood is the most important or relevant geographic context where the neighborhood effect operates. For example, Houston et al. (2004) used census block groups as neighborhood areas and observed that ethnic minorities and low-income neighborhoods are disproportionately exposed to traffic-related air pollutants in Southern California. Based on the data of people's residential census blocks, Brauer, Reynolds, and Hystad (2013) found

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that about 10 million Canadians are exposed to high levels of traffic-related air pollution.

Using residence-based fixed administrative units as neighborhood areas might be proper when the environmental factors in question largely operate in or around people's residential neighborhoods, such as collective efficacy or social capital (Sampson, Raudenbush, and Earls 1997; Sampson, Morenoff, and Earls 1999; Kwan 2018b). Using a residence-based approach to assess individual exposure to mobility-dependent environmental factors (e.g., air and noise pollution and traffic congestion), however, could lead to unreliable and even erroneous results because most people travel to areas outside of their residential neighborhoods to undertake their daily activities instead of remaining in their home neighborhoods; they are thus exposed to different neighborhood contexts (Frumkin 2006; Cummins 2007; Matthews 2008; Kwan 2012, 2013). For example, the 2017 National Household Travel Survey (NHTS) reported that on average people in the United States undertake 3.4 trips and travel about forty miles per day (Federal Highway Administration 2018). Similarly, Jones and Pebley (2014) found that the activity spaces of people in Los Angeles County include many nonresidential census tracts with characteristics that are significantly different from those of their residential census tracts. Further, mobility-dependent environmental factors vary over space and time in a highly complex manner, and people's exposures to them cannot be accurately assessed using static and fixed residential neighborhoods. For instance, air pollution concentrations are highly uneven in space and time due to the dynamics of pollutants associated with specific pollution sources (e.g., vehicular traffic) and meteorological conditions (Yoo et al. 2015; Park and Kwan 2017).

Researchers have recognized the importance of these methodological issues in neighborhood effect studies in recent years. For instance, Kwan (2012) highlighted these issues as manifestations of the uncertain geographic context problem (UGCoP) and stressed that failure to accurately delineate the true geographic context might lead to critical inferential errors when investigating the effects of environmental exposure on people's health behaviors and outcomes. Kwan (2018a) further elaborated on other challenges in accurately representing people's environmental contexts and measuring their exposures to environmental influences (e.g., the idiosyncratic and multidimensional nature of contextual effects, the frame dependence of exposure measures, and selective mobility bias).

Some studies have been conducted in recent years to specifically address the UGCoP and the contextual uncertainties when studying air pollution (Park and Kwan 2017; J. Ma, Tao, et al. 2020), the food environment (Chen and Kwan 2015), people's body weight status (Zhao, Kwan, and Zhou 2018), and substance use (Kwan et al. 2019). An important conclusion that emerged from these studies is that ignoring human daily mobility and exposures to nonresidential contexts could lead to erroneous assessments of individual exposures (e.g., Setton et al. 2011; Hurvitz and Moudon 2012; Dewulf et al. 2016; Shafran-Nathan et al. 2017; Shafran-Nathan, Yuval, and Broday 2018). A particularly important finding from this research is a specific and new kind of bias observed from comparing residence-based and mobility-based individual exposures: Mobility-based exposure estimates tend to converge to the average exposure value of the participants or the population in the study area, suggesting that "using residence-based neighborhoods to estimate individual exposures to and the health impact of environmental factors will tend to overestimate the statistical significance and effect size of the neighborhood effect" (Kwan 2018b, 2). This phenomenon is called *neighborhood effect averaging*.

The Neighborhood Effect Averaging Problem

Neighborhood effect averaging is the phenomenon that mobility-based individual exposures (MIE) tend to move closer to the average level of the participants or population in a study area when compared to residence-based individual exposures (RIE; Kwan 2018b). For instance, using the phone-based daily trajectories of about 5 million people in Belgium, Dewulf et al. (2016) found that MIE to nitrogen dioxide are higher than RIE for persons with low RIE, whereas MIE to nitrogen dioxide are lower than RIE for persons with high RIE. A study in China on individual exposures to six air pollutants by Yu, Russell, Mulholland, and Huang (2018) also observed the same phenomenon. The underlying reason for neighborhood effect averaging was first articulated by Kwan (2018b) through considering three types of situations concerning the values of RIE relative to the average value of exposures.

The first situation occurs when the RIE level for a particular individual is much higher than the average level. In this case, the person in question is more likely to visit neighborhoods where exposure levels are lower than the level in his or her residential neighborhood (Kwan 2018b). This is because the frequency distributions of individual exposure levels of the participants or population tend to follow a bell-shaped curve, which was empirically observed in previous studies (e.g., Dewulf et al. 2016; Nyhan et al. 2019). As a result, MIE tends to be lower than RIE when the latter is much higher than the average level. On the contrary, the second situation occurs when the RIE for a particular individual is much lower than the average level. In this case, the person is more likely to visit neighborhoods where exposure levels are higher than the level in his or her residential neighborhood (Kwan 2018b). As a result, MIE tends to be higher than RIE when the latter is much lower than the average level. Finally, the third situation occurs when the RIE for a particular individual is close to the average level of the participants or population. In this situation, it is highly likely that a person would experience similar levels of exposure when compared to the exposure level in his or her residential neighborhood (Kwan 2018b).

Mainly due to the first two of these situations, individual exposure levels tend to converge to the average level when people's daily mobility is considered when assessing exposures. Therefore, using a residence-based approach might overestimate the statistical significance and the effect size of neighborhood effects on the outcome variable and thus could lead to serious inferential errors. This is a serious methodological issue, which is referred to as the *neighborhood effect averaging problem* (NEAP; Kwan 2018b). It is important to note that the NEAP not only suggests that RIE and MIE levels can differ significantly but also identifies neighborhood effect averaging as a new and specific source of the UGCoP that leads to such differences. As mentioned earlier, some previous studies already found that, under certain circumstances, considering daily mobility could lead to significantly different individual exposure levels (i.e., MIE) when compared to the results obtained by a residence-based approach (i.e., RIE; e.g., Yoo et al. 2015; Park and Kwan 2017). These studies, however, did not identify neighborhood effect averaging as a specific source of these differences. Further, very few studies to date have examined how the NEAP might influence the results of studies on individual exposures to environmental influences (e.g., J. Kim and Kwan 2019; X. Ma, et al. 2020).

To bridge this significant knowledge gap, this study thus focuses on examining the NEAP. It seeks to show whether estimates of RIE differ significantly from MIE in the specific manner suggested by the NEAP. It also seeks to examine the characteristics of the individuals most affected by the NEAP, thus showing how the NEAP might affect different social groups differently, in addition to leading to erroneous results in assessments of individual mobility-dependent exposures to environmental influences.

This study examines the NEAP through an assessment of individual exposures to air pollution (ground-level ozone) using GIScience methods and an activity-travel diary data set of 2,737 individuals collected in the Los Angeles metropolitan statistical area (MSA). We focus on ambient ground-level ozone concentration as the environmental influence in this study, because it is widely known that exposure to ground-level ozone negatively affects human health (e.g., Levy et al. 2001; Health Effects Institute 2010; Ha et al. 2014). It is important to note that this research primarily seeks to conduct a methodological investigation of the NEAP, especially on how it might affect individual exposure estimates. It does not seek to examine whether individual exposures to ozone actually affect human health. Further, it is important to note that the NEAP mainly applies to mobility-dependent exposures such as air and noise pollution and traffic congestion. We do not intend to suggest that the NEAP also applies to neighborhood effects that largely operate through people's residential neighborhoods (e.g., collective efficacy).

Specifically, this study seeks to answer two main questions: (1) Does the NEAP exist when assessing individual exposures to ground-level ozone in the study area? (2) Whose estimated exposures are most affected by the NEAP? In other words, whose exposures witness a larger difference between the mobility-based and residence-based estimates? Answering these questions would provide significant evidence about the NEAP and advance our understanding of how different social groups' daily mobility might influence the extent to which their exposures are affected by the NEAP, which in turn can help

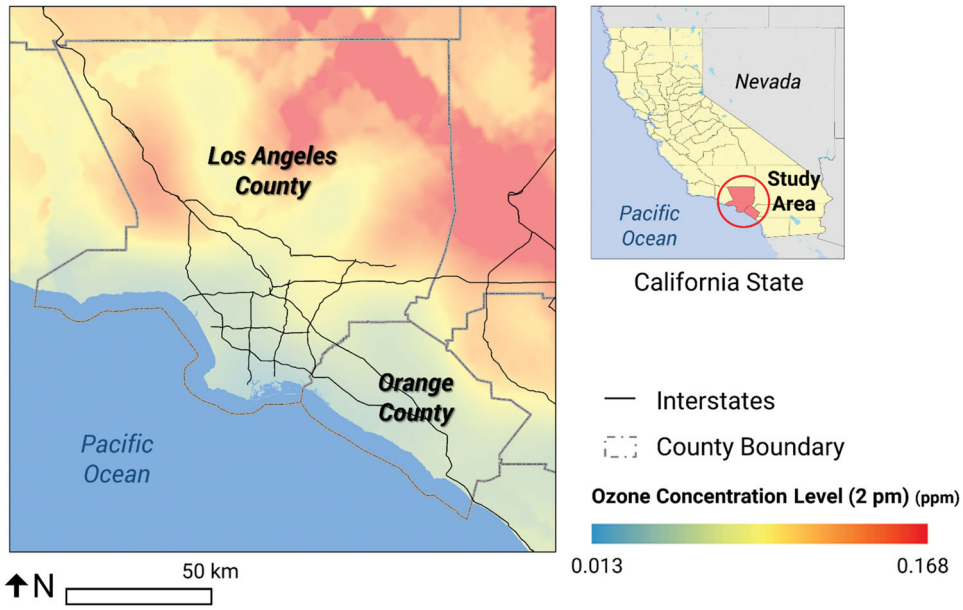

Figure 1. The Los Angeles metropolitan statistical area and the ozone concentration levels at 2 p.m. on 15 August 2018.

inform public health policies to focus on certain social groups that deserve specific attention and policy interventions.

Study Area and Data

The study area for this research is the Los Angeles–Long Beach–Anaheim MSA in California, which includes Los Angeles County and Orange County. The Los Angeles MSA is well known for its serious air pollution problems. For example, Los Angeles is ranked first in ozone concentrations and fourth in particulate matter pollution among 200 metropolitan areas in the United States (American Lung Association 2018). Many studies concluded that air pollution is one of the most serious public health hazards in Los Angeles (e.g., Jerrett et al. 2005; Künzli et al. 2005; Lurmann, Avol, and Gilliland 2015). We focus on the entire Los Angeles MSA as the study area because its size will enable us to capture almost all of the intrametropolitan trips recorded in the survey, given that the routine daily trips of most residents are within the MSA's boundary. Figure 1 shows the study area and estimated ozone concentrations at 2 p.m. on 15 August 2018.

Individual activity-travel survey data for this study come from the 2017 NHTS California Add-on conducted by the U.S. Department of Transportation. These survey data are accessed via the National Renewable Energy Laboratory (2019). People who were five years old or older could participate in the original survey, in which participants were asked to provide information about their activities and trips for one survey day. This information includes the location of their activities (e.g., geographic coordinates), the starting and ending time of their activities, and the travel modes of their trips (e.g., private vehicle, public transportation, bicycling, and walking). The participants also reported their sociodemographic characteristics, including age, gender, race, employment status, household income, family structure, and vehicle availability. The original survey sample included 55,793 participants from 26,095 households. Only 2,737 participants were included in the subsample for this study based on the following selection criteria: participants lived in the study area who were sixteen years old or older, whose designated survey day was a weekday (which better represents people's workday routines and trips), who did not use the subway for any of their trips (because ozone exposure during subway trips cannot be properly estimated), and whose surveys do not have any missing data. Note that because the original NHTS survey includes participants from the entire state of California, only a handful of the survey participants were selected for our subsample. For example, 50,090 individuals (nearly 90 percent of the original sample) were not selected because they did not live in the study area (i.e., the Los Angeles MSA).

Table 1. Comparison of the sociodemographic characteristics of the selected individuals with those of the Los Angeles MSA

Variables	Selected participants (2,737 individuals)			Los Angeles MSA[a]		
Gender	Male		Female	Male		Female
	48%		52%	49%		51%
Race	White[b]	African American	Asian	White	African American	Asian
	55%	5%	16%	54%	7%	16%
Employed %		60%			60%	
Low-income household %[c]		13%			20%	

Notes: MSA = metropolitan statistical area.
[a]American Community Survey 2017 five-year estimates (people who are sixteen years old and older).
[b]Non-Hispanic white.
[c]Household income less than $25,000 per year is considered low income.

Table 1 compares the sociodemographic characteristics of these selected participants with those of the population of the Los Angeles MSA in 2017. Overall, the 2,737 selected participants and the population of the Los Angeles MSA are similar in gender and racial composition as well as employment status. A lower proportion of low-income households (13 percent) is included in our subsample, however. This might be due to the lower participation rate of low-income households in the original survey. For example, 17 percent of the households who participated in the original NHTS from California are low-income households, whereas 19 percent of the households in California are low-income households. This, in turn, can be explained by the fact that minority groups tend to be underrepresented in activity-travel surveys (H. Kim et al. 1993; Barajas, Chatman, and Agrawal 2018).

Data for estimating ozone concentrations in this study are from the hourly ground-level ozone (O_3) and nitrogen oxides (NO_x) data from twenty-six monitoring stations and the hourly temperature data from eighty-one monitoring stations in the South Coast Air Basin, which largely overlaps the study area. These data were collected by the California Air Resources Board. We use hourly (0–23 hours) ozone, nitrogen oxides, and temperature measurements on 15 August 2018, which is a randomly selected weekday in summer. Summer is selected because it provides relatively favorable conditions (strong sunlight and low wind speed) for the formation of ground-level ozone. Note that although the activity-travel survey data were collected one year earlier, they still reflect people's routine daily activities and trips in general and can be used with 2018 ozone data for a methodological investigation that compares RIE and MIE to ozone.

Methods

Measuring Residence-Based and Mobility-Based Individual Exposures

To derive individual exposures to ozone using either the residence-based or mobility-based approach, we first generate a ground-level ozone concentration surface for each of the twenty-four hours of a day using co-kriging estimation and the hourly data on ground-level ozone, nitrogen oxides, and temperature. Co-kriging, which is an extension of kriging, is a geospatial estimation method widely used for air pollution modeling (e.g., Phillips et al. 1997; Singh et al. 2011; Park and Kwan 2017). We choose kriging over other methods—such as land use regression, dispersion models, or interpolation methods (Berman et al. 2015; Yu, Russell, Mulholland, Odman, et al. 2018)—because of the large size of the study area (14,770 km^2) and the higher temporal resolution (one hour) of the ozone surfaces we intend to generate. In the co-kriging estimation, temperature and nitrogen oxides are used as the secondary variables, which have strong relationships with the primary variable of ground-level ozone concentrations (Phillips et al. 1997; Park and Kwan 2017).

Different variogram models (e.g., Gaussian, exponential, or spherical) and model parameters (e.g., nugget, sill, and range) are assessed to obtain the model with the best performance as evaluated by root mean square error. Co-kriging estimation is repeated twenty-four times (0–23 hours) to estimate hourly ground-level ozone concentrations at a 1 km^2 resolution. Because the 1 km^2 spatial resolution is used for ozone surface modeling in this study, it implies that a person is exposed to the same ozone level if he or she travels within 1 km. The Gaussian variogram model that yields the lowest root mean

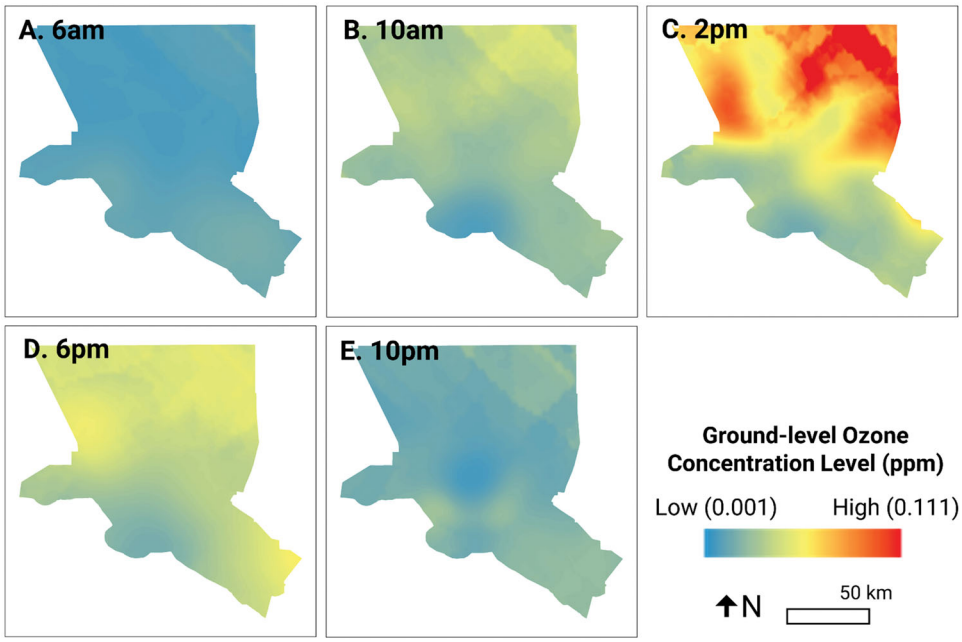

Figure 2. Estimated hourly ground-level ozone concentration surface (selected hours).

square error and a cross-validated R^2 of 0.87 is finally chosen. Figure 2 shows five hourly ground-level ozone concentration surfaces estimated with this co-kriging model. Overall, the spatiotemporal patterns of ozone concentrations in the study area corroborate earlier observations from other sources (e.g., California Environmental Protection Agency 2014; Park and Kwan 2017): Ozone concentrations are highest in the middle of a day (e.g., 2 p.m.) because of strong sunlight, and areas with high ozone concentrations are largely in the inland portion of the study area because wind blows mostly from the west toward inland areas.

Based on these twenty-four hourly ozone concentration surfaces, we measure individual exposures to ozone using the activity-travel diary data and the following formulation:

$$E_i = \sum_{t=1}^{1440} C(x_t, y_t, t), \tag{1}$$

where E_i represents individual i's cumulative exposure to ozone for one day (1,440 minutes). $C(x_t, y_t, t)$ is the ozone concentration level at location (x_t, y_t) at time t (at one-minute intervals) estimated by the co-kriging model. Note that although co-kriging is estimated on an hourly basis (i.e., assuming that the ozone level at a location is constant for one hour), we measure individual exposures at one-minute intervals because an individual's location can be different even within a one-hour interval, because he or she might travel to places where the ozone levels are considerably different. Moreover, we assume that air pollution levels in different microenvironments (e.g., indoors) are the same as the outdoor levels estimated by co-kriging due to data limitations.

We adopt two different approaches to define the location of an individual (x_t, y_t) at time t: a residence-based approach and a mobility-based approach. In the residence-based approach, we assume that individual i stays at his or her residential location, which is extracted from the survey data. In the mobility-based approach, individual i's space-time path for the survey day is constructed based on the activity-travel diary data using geographic information systems and the time-geographic framework developed by Hägerstrand (1970) and his colleagues (e.g., Parkes and Thrift 1975; Lenntorp 1976, 1999; Miller 1999; Kwan 1998).

Because the original survey data do not have information about the actual routes participants used to travel between activity locations, we derive travel routes based on the assumption that participants used the routes with the shortest travel time for the travel mode (e.g., driving, riding the bus, biking, and walking) they reported for each trip. To generate more realistic routes, we use the Google Maps application programming interface (Google 2019), which takes into account the characteristics of real transportation networks (e.g., detailed road networks including local roads, public transit networks based on actual routes and schedules, and local pedestrian

A. A person's daily activity-travel diary

Trip ID	Origin (x, y)	Destination (x, y)	Departure Time	Travel Mode
1	Home (x_1, y_1)	Work (x_2, y_2)	8:00 am	Driving
2	Work (x_2, y_2)	Home (x_1, y_1)	5:00 pm	Driving
3	Home (x_1, y_1)	Gym (x_3, y_3)	7:30 pm	Transit
4	Gym (x_3, y_3)	Shop (x_4, y_4)	9:00 pm	Walk
5	Shop (x_4, y_4)	Home (x_1, y_1)	10:20 pm	Walk

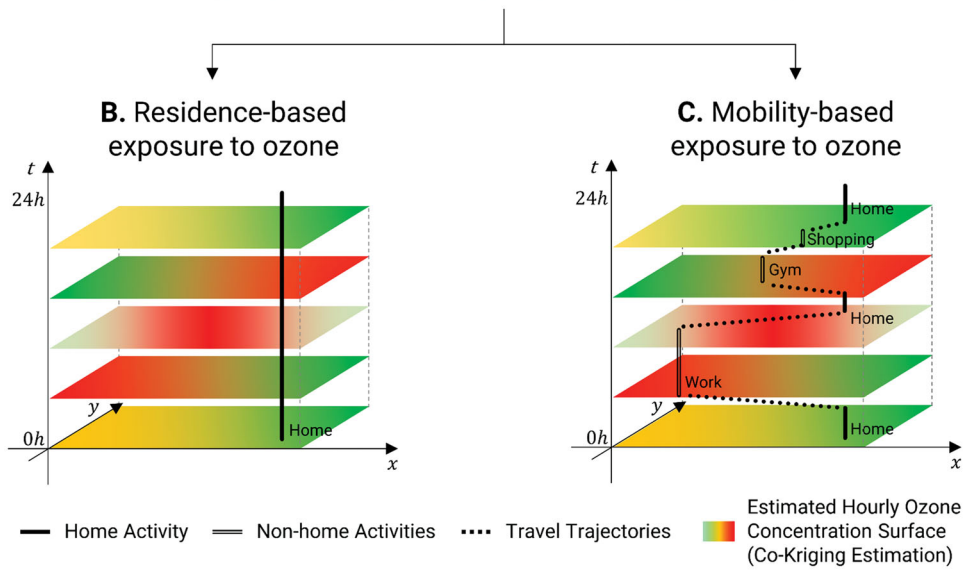

Figure 3. A schematic illustration of a person's (A) one-day activity-travel diary; (B) residence-based ozone exposure, assuming that the person stays at his or her home during the survey day; and (C) mobility-based ozone exposure that considers the person's space-time path for the day.

and bike routes) and the traffic congestion level on each road segment estimated at twenty-minute intervals (e.g., J. Kim and Kwan 2019; J. Kim and Lee 2019). It also provides travel time estimates for different travel modes (e.g., driving and biking). With respect to the detailed traffic congestion level on each road segment, the API estimates the congestion level by using the crowdsourced real-time traffic data obtained from anonymized cell phone users who drive on the road and consent to provide their real-time location information to Google (Barth 2009). Figure 3 shows the fictitious activity-travel diary of an individual and illustrates how this person's RIE and MIE to ozone are obtained in this study.

Examining the Neighborhood Effect Averaging Problem

We use three methods to examine how the NEAP is manifested when assessing individual ozone exposures. First, using descriptive statistics, we examine whether there is a decrease in the standard deviation and the range between the top and bottom quantiles of the MIE levels when compared to the RIE. We also use a paired sample *t* test to examine whether participants' RIE and MIE are significantly different. Second, using a scatterplot, we analyze whether the participants with high RIE tend to experience lower MIE and whether the participants with low RIE tend to experience higher MIE. The scatterplot shows the relationship between the standardized (z score) RIE levels (x-axis values) and how much the RIE levels are higher or lower than the MIE levels (y-axis values). Third, we compare the frequency distributions (histograms) of the RIE and MIE levels to assess whether there is a tendency for the MIE to converge to the average exposure value.

Examining the Association between Individuals' Sociodemographic Characteristics and the Level of Neighborhood Effect Averaging

We use the following measure to assess the extent to which an individual's exposure is

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

Variables		Description	M (*SD*) or percentage
NEA		Degree of neighborhood effect averaging	1.6 (2.4)
Age		Age	49.7 (17.7)
Male		1 = male, 0 = female	48.2%
Children		1 = having young children (age: 0–4), 0 = otherwise	9.1%
Immigrant		1 = immigrant; 0 = nonimmigrant	27.7%
Race[a]	*Black*	1 = African American; 0 = otherwise	5.4%
	Asian	1 = Asian, 0 = otherwise	16.1%
	Others	1 = others, 0 = otherwise	11.5%
Hispanic		1 = Hispanic/Latino, 0 = otherwise	19.7%
Employed[b]		1 = employed, 0 = otherwise	59.5%
Income[c]		Household income level (1: low–11: high)	6.2 (2.7)

Notes: $n = 2{,}737$.
[a]Base = White.
[b]Otherwise = including the unemployed, homemakers, students, and the retired.
[c]Income Level 1 = <$10,000; Level 2 = $10,000–$14,999; Level 3 = $15,000–$24,999; Level 4 = $25,000–$34,999; Level 5 = $35,000–$49,999; Level 6 = $50,000–$74,999; Level 7 = $75,000–$99,999; Level 8 = $100,000–$124,999; Level 9 = $125,000–$149,999; Level 10 = $150,000–$199,999; Level 11 = $200,000+.

affected by neighborhood effect averaging (Equation 2):

$$NEA_i = \left|E_i^R - E_i^M\right|, \tag{2}$$

where NEA_i denotes the degree of neighborhood effect averaging for individual i. E_i^R and E_i^M denote individual i's RIE and MIE. A higher value of neighborhood effect averaging means that the person in question visits nonresidential neighborhoods where ozone levels are considerably higher or lower than the level in his or her residential neighborhood in a way that moves his or her MIE closer to the average level of the participants.

Further, we examine whether certain sociodemographic characteristics are associated with a higher degree of neighborhood effect averaging using a spatial error model with the form of Equation 3 (note that the dependent variable is log-transformed). The description of the variables in the model is provided in Table 2.

$$\begin{aligned} NEA_i = {} & \beta_0 + \beta_1 Age_i + \beta_2 Male_i + \beta_3 Children_i \\ & + \beta_4 Immigrant_i + \beta_5 Black_i + \beta_6 Asian_i \\ & + \beta_7 Others_i + \beta_8 Hispanic_i + \beta_9 Employed_i \\ & + \beta_{10} Income_i + \lambda W \varepsilon_i + u_i, \end{aligned} \tag{3}$$

where λ is the spatial lambda, W is the spatial weight matrix (K–5 nearest neighbors), and ε_i is the spatial component of the error term. We choose spatial regression instead of ordinary least squares (OLS) regression because of the presence of spatial autocorrelation in the OLS residuals. The Moran's I of the OLS residuals is 0.064, which is statistically significant ($p < 0.001$). The spatial error model is selected as the Lagrange multiplier diagnostics suggest (Anselin 1988). We also examine the multicollinearity among the independent variables using the variance inflation factor (VIF). Variables with a VIF value higher than 10 are considered strongly correlated (O'Brien 2007). In our model, all independent variables have a VIF value of less than 10, suggesting that there is no significant multicollinearitybetween them. Moreover, we choose the K-nearest neighbor spatial weight matrix over other types of weight matrices, such as the contiguity matrices (e.g., rook type, queen type) and the great-distance matrices. This is because the data employed in the model are individual-level point data, which makes it difficult to define a contiguity-type spatial weight matrix. Moreover, because the maximum value of the distance to the nearest point (i.e., the minimum threshold for the great-distance matrix to avoid island effects) is nearly 20 km, the great-distance-type spatial weight matrix might not work effectively. Thus, we select the K-nearest neighbors spatial weight matrix. In the spatial regression analysis, four different numbers of neighbors—five, seven, nine, and eleven—are tested, and they provided nearly the same direction for the coefficients and significance levels. Therefore, we present the results of the spatial regression model using the K–5 nearest neighbors as the spatial weight matrix.

Table 3. Descriptive statistics of the residence-based and mobility-based exposures to ozone

Statistics		Residence-based individual exposures (RIE)	Mobility-based individual exposures (MIE)
M (ppm)		31.09	30.76
SD		5.17	4.89
Maximum (ppm)		52.99	53.15
Minimum (ppm)		20.04	20.39
Range between	Maximum and minimum	32.95	32.76
	1st and 99th quantile	27.03	26.97
	2.5th and 97.5th quantile	23.37	22.86
	5th and 95th quantile	18.13	16.75
	7.5th and 92.5th quantile	13.94	13.20
	10th and 90th quantile	11.51	10.82

Note: $n = 2{,}737$.

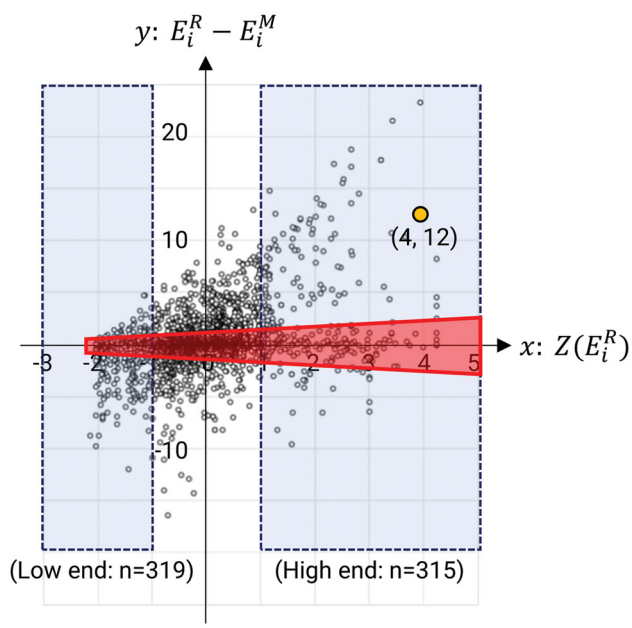

Figure 4. A scatterplot that shows the x-axis values as the standardized (z score) residence-based individual exposure level and the y-axis values obtained by subtracting the mobility-based exposure from the residence-based exposure ($n = 2{,}737$).

Results

Descriptive Statistics of Residence-Based and Mobility-Based Exposures to Ozone

Descriptive statistics of the estimated RIE and MIE to ozone are shown in Table 3. As indicated in Table 3, the standard deviation of individual exposures decreases from 5.17 to 4.89 when daily mobility is considered. This indicates that there is less variation in the MIE when compared to the RIE, suggesting a likely tendency for MIE to converge toward the average level. Table 3 also shows the ranges between the top and bottom quantiles for the RIE and MIE. It shows that the ranges between the top (i.e., maximum, 1st, 2.5th, 5th, 7.5th, and 10th) and the bottom (i.e., minimum, 99th, 97.5th, 95th, 92.5th, and 90th) quantiles are smaller for the MIE than the RIE, indicating that the MIE have smaller ranges (i.e., less variation) and a tendency of leaning toward the mean when compared to the RIE.

Although the differences between the RIE and MIE shown in Table 3 seem slight, the paired sample t test indicates that the pairwise differences (for each participant in the subsample) between the RIE and MIE are statistically significant ($p < 0.001$). This result corroborates the findings in previous studies that compared individual air pollution exposure levels based on a residence-based approach and a mobility-based approach (e.g., Dewulf et al. 2016; Park and Kwan 2017; Yu, Russell, Mulholland, and Huang 2018; J. Ma et al. 2020). It also calls for further investigation of how neighborhood effect averaging is manifested for the selected participants, which the following two subsections seek to undertake.

Patterns of Neighborhood Effect Averaging

The scatterplot shown in Figure 4 reveals the relationship between the standardized (z score) RIE (x-axis values) and how much the RIE is higher or lower than the MIE (by subtracting the MIE from the RIE and showing the differences as the y-axis values) for the participants. For example, point (4, 12) highlighted in Figure 4 indicates a person whose standardized RIE is 4, which is 12 ppm higher than his or her MIE. Further, a dot in the red

zone indicates a participant for whom the relative (percentage) difference between his or her RIE and MIE is less than 5 percent. When this occurs, we consider the RIE and MIE as basically the same.

As shown in Figure 4, as the standardized RIE level (x value) increases, there are more dots with positive and higher y values than dots with negative and lower y values. Note that a positive y value indicates that the RIE level is higher than the MIE level and vice versa. Figure 4 thus shows that participants with higher RIE tend to experience lower MIE, whereas participants with lower RIE tend to experience higher MIE, indicating that there is neighborhood effect averaging. In what follows, we focus on the participants in the low and high ends of the standardized RIE.

At the low end, there are 319 participants whose standardized RIE levels are lower than -1 (the blue rectangle on the left in Figure 4). These 319 individuals are participants whose RIE levels are lower than the average level by one standard deviation or more. Among these 319 individuals, 140 have an MIE level significantly different (i.e., more than 5 percent difference) from his or her RIE level. Among these 140 individuals, there are 116 individuals (83 percent) whose MIE are higher than their RIE. This indicates that for participants whose RIE are lower than the average level by one or more standard deviations, it is much more likely that their MIE are higher than their RIE.

At the high end, there are 315 participants whose standardized RIE levels are higher than 1 (the blue rectangle on the right in Figure 4). These 315 individuals are participants whose RIE levels are higher than the average level by one standard deviation or more. Among these 315 individuals, 137 individuals have an MIE level significantly different (i.e., more than 5 percent difference) from their RIE level. Among these 137 individuals, there are 112 individuals (82 percent) whose MIE are lower than their RIE. This indicates that for participants whose RIE are higher than the average level by one or more standard deviations, it is much more likely that their MIE are lower than their RIE. The results revealed in Figure 4 thus clearly identify two specific manifestations (in the low and high ends) of neighborhood effect averaging for the participants in our subsample. They also corroborate the findings from previous studies that examined the patterns of estimation errors when daily mobility is ignored in air pollution exposure studies (e.g., Dewulf et al. 2016; Yu, Russell, Mulholland, and Huang 2018).

Some might argue that these results do not lend strong support for the existence of the NEAP because the RIE and MIE are similar for many participants (1,890 participants, 69 percent of our subsample). Note, though, that the paired sample t test showed that the RIE and MIE are significantly different ($p < 0.001$) for the participants based on pairwise comparisons. Further, note that the NEAP might not affect the entire population evenly. It mainly occurs for people whose RIE levels are very high or very low and who move around in their daily lives considerably and are thus exposed to various nonresidential neighborhood contexts with ozone levels that are considerably different from those in their residential neighborhoods.

In this light, it should be noted that not all participants in our subsample have significant daily mobility. For instance, for the 1,890 participants in our subsample whose RIE and MIE are similar, the average distance of their out-of-home activity locations from their home is 3.89 km. Given the patterns of spatial variation in ground-level ozone concentrations in the study area (Figure 2), this distance is likely too short for these low-mobility participants to be exposed to ozone levels that are significantly different from those in their residential neighborhoods. On the contrary, the average distance of the out-of-home activity locations from the home of the other 847 participants whose RIE and MIE are significantly different is 11.04 km. This average distance between activity locations and home is almost three times that of the low-mobility group and seems long enough for these high-mobility participants to be exposed to ozone levels that are considerably different from those in their residential neighborhoods. These observations help explain the role of individual mobility in neighborhood effect averaging and support our argument that the results shown in Figure 4 still provide strong evidence for the existence of neighborhood effect averaging.

The histograms and the probability density functions of the RIE and MIE of the participants ($n = 2{,}737$) shown in Figure 5 present further evidence for the existence of neighborhood effect averaging. Note that when compared to the RIE, both the histogram and probability density function of the MIE have a slight tendency to converge to the mean value. In Figures 5A and 5B, the histograms indicate that more individuals experienced exposure levels close to the average level, and the mobility-based

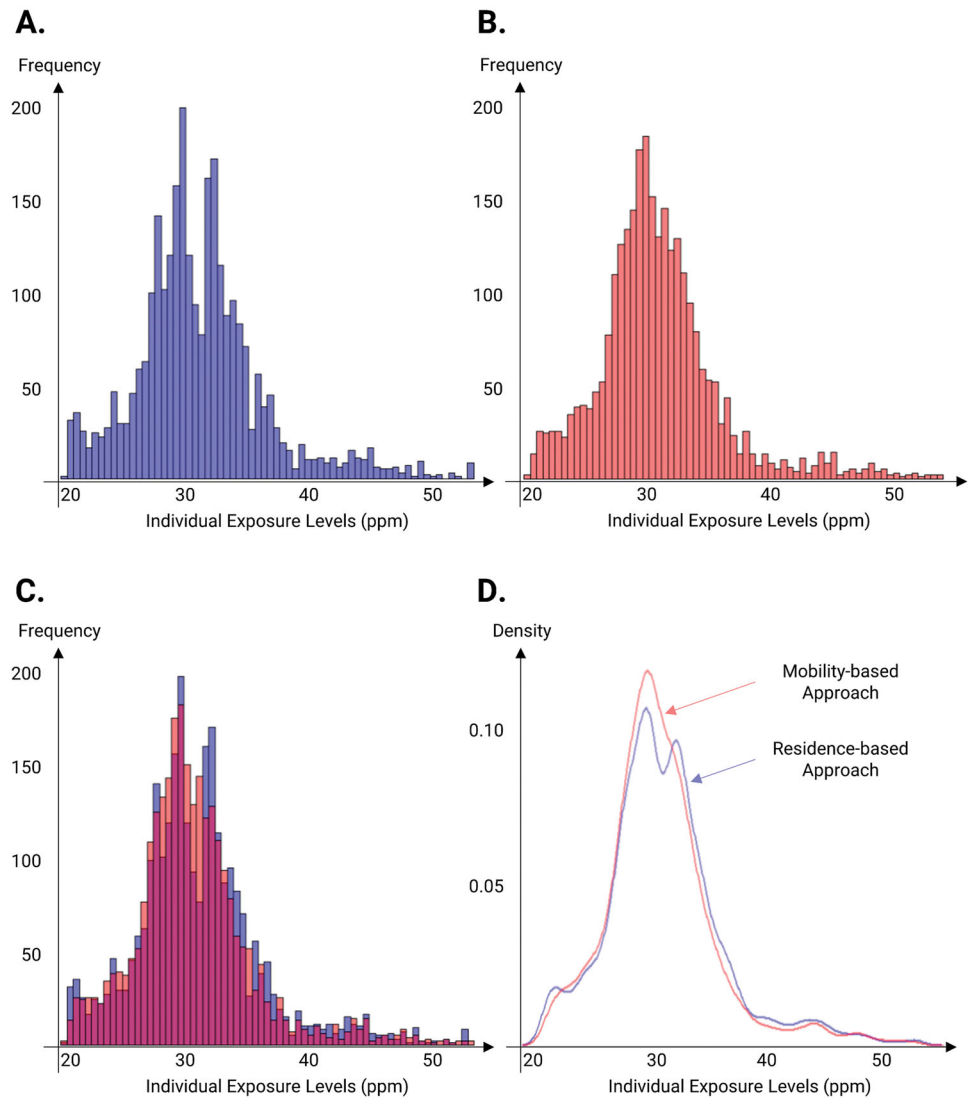

Figure 5. Histograms of individual exposures ($n = 2{,}737$) based on (A) the residence-based approach; (B) the mobility-based approach; (C) the two histograms overlaid; and (D) the probability density functions (blue line = residence-based approach; red line = mobility-based approach).

histogram (Figure 5B) has a shape closer to a bell-shaped distribution when compared to the residence-based histogram (Figure 5A). The probability density functions in Figure 5D also yield a similar observation. When compared to the probability density function of the RIE, the probability density function of the MIE has slightly lower frequencies in both the low and high ends, although it has moderately higher frequencies near the mean value of 31, providing clear evidence for the existence of neighborhood effect averaging.

To sum up, the results of this analysis based on the scatterplot, histograms, and probability density functions corroborate those obtained by descriptive statistics reported earlier. Based on these results, we conclude that neighborhood effect averaging indeed exists for the participants when assessing their individual ozone exposures in the study area.

Results of the Spatial Regression Analysis

In this subsection, we present the results of the spatial regression analysis on the associations between individuals' sociodemographic characteristics and the degree of neighborhood effect averaging experienced. The dependent variable is the degree of neighborhood effect averaging pertinent to the exposure estimates of individual i, which is NEA_i as described in Equation 2. The descriptive statistics of the dependent and independent variables (e.g., age,

gender, and race) used in the spatial error model were presented in Table 2.

Table 4 shows the results of the spatial error model. Specifically, the independent variables that have a significant positive association with the degree of neighborhood effect averaging include being male ($p < 0.05$), being employed ($p < 0.001$), and having a higher income ($p < 0.01$). The only independent variable that has a significant negative association with the degree of neighborhood effect averaging is age ($p < 0.01$). In other words, high income, being employed, being younger, and being male are associated with a higher degree of neighborhood effect averaging when compared to the other groups (i.e., low income, nonworking, being older, and being female). Further, the result indicates that there is no significant association between the degree of neighborhood effect averaging and an individual's having children, immigrant status, and race.

Table 4. Results of the spatial error model on the association between individual sociodemographic characteristics and the level of neighborhood effect averaging experienced

Variables		Coefficient	*SE*	*p* Value
Age		–0.004	0.001	0.001**
Male		0.086	0.041	0.034*
Children		–0.034	0.074	0.647
Immigrant		–0.025	0.053	0.640
Race[a]	*Black*	0.122	0.097	0.206
	Asian	–0.103	0.068	0.127
	Others	–0.118	0.071	0.096
Hispanic		0.054	0.061	0.376
Employed		0.567	0.044	0.000***
Income		0.029	0.008	0.001**
λ		0.143	—	0.000***
Intercept		–0.742	0.104	0.000***

Notes: [a]Base = White.
Akaike's information criterion = 8,143.7, log-likelihood = –4,058.867, $n = 2{,}737$
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

We also explore why age, gender, income, and employment status are associated with the degree of neighborhood effect averaging for an individual. Because neighborhood effect averaging is mainly influenced by a person's daily mobility, we hypothesize that individuals who have a high income and who are younger, employed, and male tend to have a higher level of daily mobility, which will lead to a higher degree of neighborhood effect averaging. To test this hypothesis, we conduct the following two analyses.

First, we examine whether age, gender, income, and employment status are associated with a higher level of daily mobility. Following an approach in previous studies (Setton et al. 2011; Yoo et al. 2015; Shafran-Nathan et al. 2017), individual daily mobility is measured by the average distance of out-of-home activity locations from home ($Distance_i$) and the total duration of out-of-home activities ($Duration_i$). A higher value of these variables indicates a higher level of daily mobility. We use two spatial error models with $Distance_i$ and $Duration_i$ as the dependent variable, respectively, and age, gender, income, and employment status as the independent variables.

Table 5 shows the results of this analysis. In both Model 1 and Model 2, the independent variables that have a significant positive association with participants' daily mobility include being male, being employed, and income. Moreover, the only independent variable that has a significant negative

Table 5. Results of the spatial error models on the association between the selected sociodemographic variables and the level of daily mobility ($Distance_i$ and $Duration_i$)

	Model 1 (Dependent variable: $Distance_i$)[a]			Model 2 (Dependent variable: $Duration_i$)[b]		
Variables	Coefficient	*SE*	*p* Value	Coefficient	*SE*	*p* Value
Age	–0.022	0.009	0.011*	–2.549	0.220	0.000***
Male	1.077	0.282	0.000***	19.607	7.479	0.009**
Employed	3.052	0.308	0.000***	212.070	8.046	0.000***
Income	0.145	0.057	0.011*	3.706	1.409	0.009**
λ	0.239	—	0.000***	0.051	—	0.101
Intercept	3.836	0.661	0.000***	317.389	16.495	0.000***

Notes: $n = 2{,}737$.
[a]Akaike's information criterion = 18,793; log-likelihood = –9,389.371.
[b]Akaike's information criterion = 36,627; log-likelihood = –18,306.45.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

association with participants' daily mobility is age. All variables are significant at the 5 percent level. These results indicate that higher income, being employed, being male, and being younger are significantly associated with a higher level of daily mobility, which seems to support the spatial entrapment hypothesis (England 1993; McLafferty and Preston 1996; Kwan 1999; Rapino and Cooke 2011), which argues that socially disadvantaged groups (e.g., low-income people and women) experience more mobility constraints in their daily lives, which in turn limits their access to jobs and urban opportunities. In addition, these results in general corroborate the findings from previous studies and nationwide travel surveys that found similar associations between individuals' daily mobility level and age, gender, income, and employment status (e.g., Federal Highway Administration 2014, 2018, 2019; Matz, Stieb, and Brion 2015; Klous et al. 2017). A recent study in China also found that low-income people, blue-collar workers, and older adults have lower daily mobility when compared to other social groups, which limits their travel outside their residential neighborhoods (X. Ma et al. 2020).

Second, we examine whether a higher level of daily mobility is associated with a higher degree of neighborhood effect averaging using a spatial error model, where NEA_i (level of neighborhood effect averaging) is the dependent variable and $Distance_i$ and $Duration_i$ (level of daily mobility) are the independent variables. The spatial error model is chosen because of the presence of spatial autocorrelation in the residuals of the OLS regression model (Moran's $I = 0.067$, $p < 0.01$). The results indicate that the level of neighborhood effect averaging is positively associated with $Distance_i$ ($\hat{\beta} = 0.045$, $p < 0.001$, $SE = 0.036$) and $Duration_i$ ($\hat{\beta} = 0.002$, $p < 0.001$, $SE = 0.000$), while controlling spatial autocorrelation ($\lambda = 0.151$, $p < 0.001$). The results thus indicate that a higher level of daily mobility is significantly associated with a higher degree of neighborhood effect averaging, which is the central argument underlying the NEAP.

Based on these results, we therefore conclude that individuals with high income, who are employed, who are younger, and who are male (compared to low-income, nonworking and older individuals, and females) are associated with a higher degree of neighborhood effect averaging because they have a higher level of daily mobility.

Spatiotemporal Patterns of Individual Ozone Exposures

To further examine how neighborhood effect averaging operates, we explore the hourly ozone exposures and space-time paths of seventy-one individuals who live in the same residential neighborhood (Santa Clarita, California). Note that the RIE of these individuals are similar other because they live in the same neighborhood. Figure 6 presents the hourly ozone exposures of these seventy-one individuals with respect to their employment status (employed vs. nonworking) and income level (high income vs. low income), which are key sociodemographic variables that are significantly associated with the level of neighborhood effect averaging. These temporal patterns reveal considerable daytime (6–18 hours) variations in exposure levels when compared to the variations in exposure levels in other time segments, indicating that these seventy-one individuals undertake many activities during daytime in neighborhoods where ozone levels differ considerably from those in their residential neighborhoods. On the other hand, there is little variation in individual ozone exposures in the early-morning or late-night hours, suggesting that these individuals tend to stay in their residential neighborhoods during these time segments.

For the seventy-one selected individuals, different employment statuses and income levels are associated with different temporal patterns of ozone exposures. Figures 6A and 6C show that there are more variations in the exposure levels of the employed and high-income individuals than those of the nonworking (Figure 6B) and low-income (Figure 6D) groups. This indicates that high-income and employed individuals tend to experience a wider range of ozone exposures over the course of a day, suggesting that the mobility-based exposures of these individuals are associated with higher levels of neighborhood effect averaging, which corroborates our earlier findings. Further, given that the ozone level of their home neighborhood (Santa Clarita) is higher than the average level of the study area, the graphs show that employed and high-income individuals (i.e., people with higher mobility) have a higher tendency to be exposed to lower ozone levels when compared to the ozone levels in their home neighborhoods over the course of a day, again indicating neighborhood effect averaging (Figures 6A and 6C).

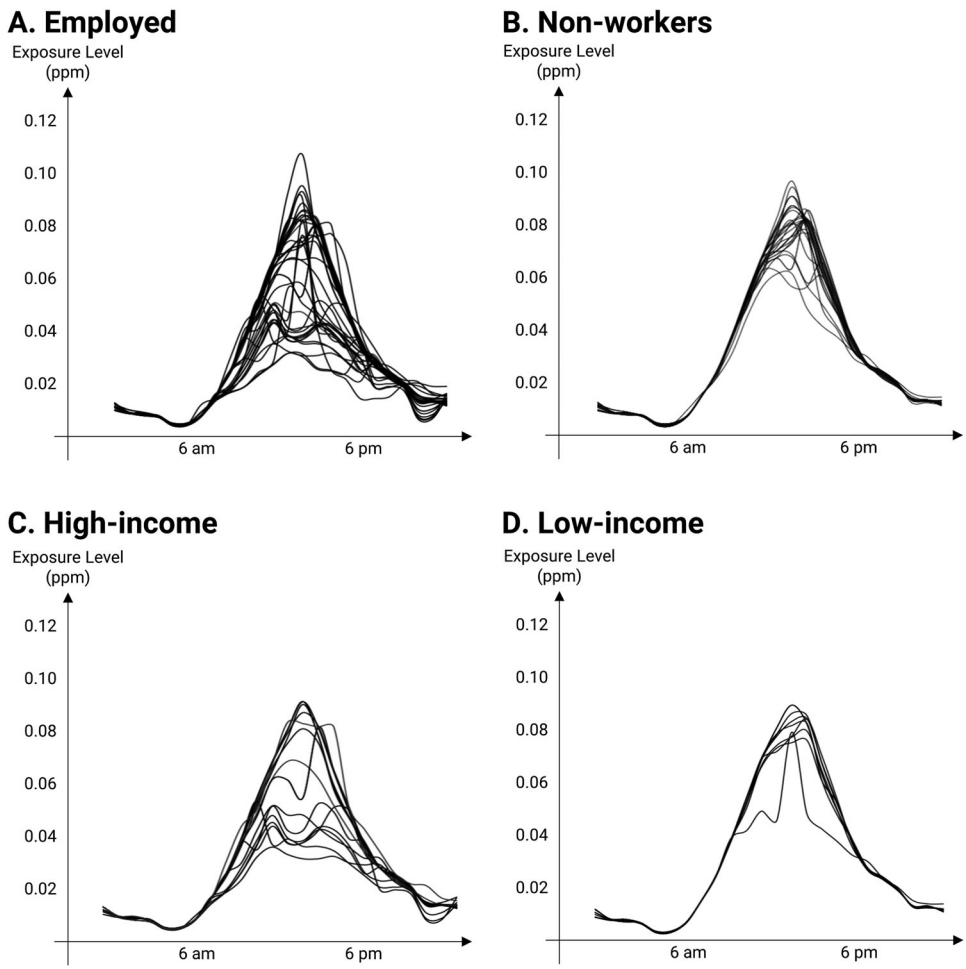

Figure 6. Hourly estimated ozone exposures of seventy-one individuals who live in Santa Clarita: (A) the employed ($n = 41$); (B) the nonworking group (the unemployed, homemakers, students, and the retired; $n = 30$); (C) the high-income group (annual household income higher than \$150,000; $n = 16$); (D) the low-income group (annual household income lower than \$50,000) people ($n = 9$).

Further, we conduct three-dimensional geovisualizations of the space-time paths of these seventy-one individuals using ArcScene (Figure 7). The space-time paths reveal that employed and high-income individuals have higher daily mobility and spend more time in undertaking out-of-home activities in nonresidential neighborhoods that are farther away from their residential neighborhoods than those of the nonworking and low-income groups. This observation also corroborates our findings from the spatial regression analysis. The results of this study thus clearly indicate that the mobility-based exposures of employed and high-income people (when compared to other less mobile social groups such as the unemployed, homemakers, students, and the retired) are associated with a higher degree of neighborhood effect averaging because they have higher daily mobility over the course of a day.

Conclusion and Discussion

This study has examined the neighborhood effect averaging problem (NEAP) by comparing the residence-based individual exposures (RIE) and mobility-based individual exposures (MIE) to ozone of 2,737 individuals in the Los Angeles MSA and demonstrated how the NEAP is significantly associated with people's daily mobility using an activity-travel data set. It found that RIE and MIE are significantly different. Individuals with high RIE tend to experience lower MIE, whereas individuals with low RIE tend to experience higher MIE. Examination of the frequency distributions of individual exposures bore out two major suggestions of the NEAP: The frequency distributions of individual exposures are similar to bell-shaped curves and the frequencies of MIE are lower than the frequencies of the RIE in the low

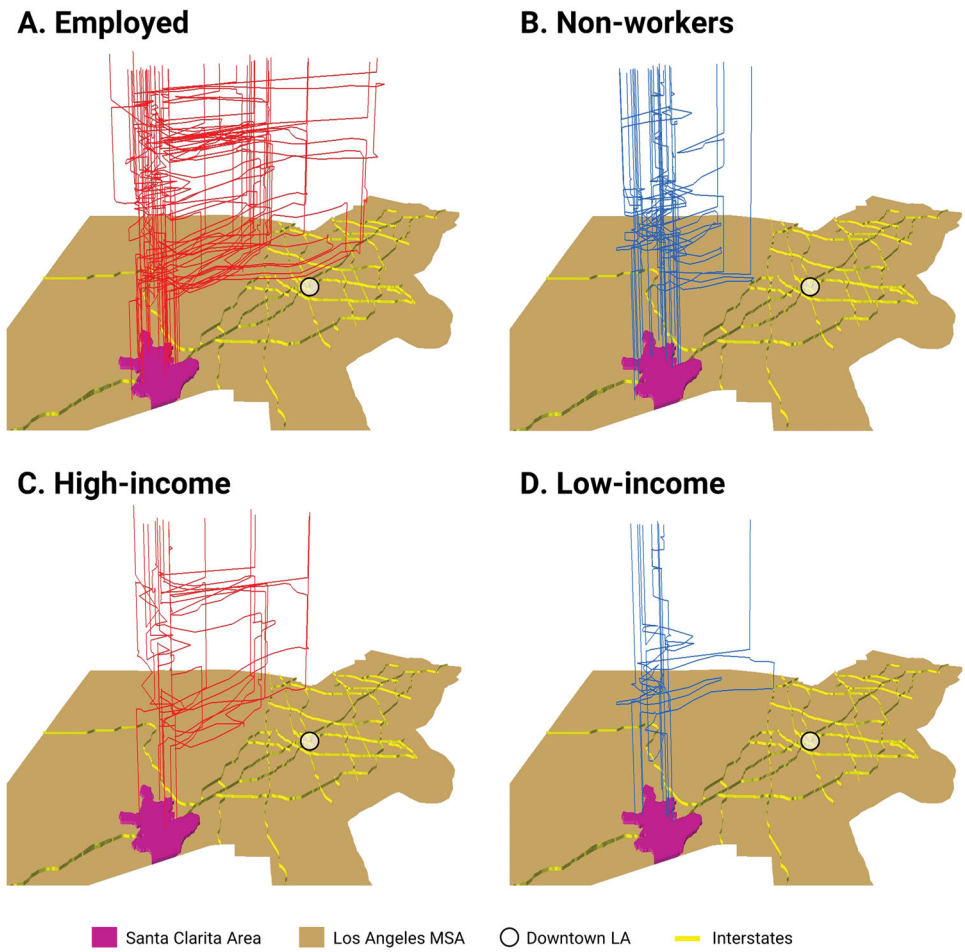

Figure 7. The space-time paths of the seventy-one individuals in Santa Clarita: (A) the employed ($n = 41$); (B) the nonworking group (the unemployed, homemakers, students, and the retired; $n = 30$); (C) the high-income group ($n = 16$); (D) the low-income group ($n = 9$). *Note:* z-axis represents time of day.

and high ends of the distributions, with moderately higher frequencies near the average value. All of these observations were supported by the results of the statistical analysis, indicating a clear tendency for MIE to converge to the mean exposure level and the existence of neighborhood effect averaging. This, in turn, suggests that using residence-based neighborhoods to estimate individual exposures to mobility-dependent environmental factors will "tend to overestimate the statistical significance and effect size of the neighborhood effect" (Kwan 2018b, 2).

The results obtained with spatial regression analysis revealed that having a high income, being employed, being younger, and being male are significantly associated with higher levels of neighborhood effect averaging when compared to the other groups (i.e., the low-income, nonworking, older, and female groups). Further, individuals who have a high income and are employed, younger, and male have higher levels of daily mobility when compared to the other groups, and individuals with higher daily mobility are associated with higher levels of neighborhood effect averaging. Examination of the spatio-temporal patterns of ozone exposures of seventy-one individuals who live in the same neighborhood clearly showed that employed and high-income individuals tend to spend more time in undertaking out-of-home activities in nonresidential neighborhoods and are thus exposed to considerably different ozone levels over the course of a day (when compared to the ozone levels in their home neighborhoods), corroborating the findings from the spatial regression analysis.

These results have important implications for all studies on mobility-dependent exposures such as air and noise pollution or traffic congestion. First, studies on mobility-dependent exposures need to address the NEAP by considering human daily mobility;

otherwise, assessments of individual exposures could be erroneous. Second, ignoring human mobility when examining social inequalities in environmental exposures might misinform policymakers (e.g., Shareck, Frohlich, et al. 2014; Shareck, Kestens, et al. 2014; Elliott and Smiley 2019; Sampson 2019). Policymakers should be aware of the effects of neighborhood effect averaging on individual exposures when formulating policy interventions to address the specific needs of disadvantaged social groups: High daily mobility might attenuate people's high exposures in their residential neighborhoods, but low daily mobility would prevent certain socially disadvantaged groups from avoiding the high exposures in their residential neighborhoods (X. Ma et al. 2020).

Specifically, it is important to recognize that some social groups might be doubly disadvantaged. For example, the spatial entrapment hypothesis argues that socially disadvantaged groups (e.g., low-income people and women) experience more mobility constraints in their daily lives, which in turn limits their access to jobs and urban opportunities (England 1993; McLafferty and Preston 1996; Kwan 1999; Rapino and Cooke 2011). When these groups live in neighborhoods with high pollution levels, there is little neighborhood effect averaging for them: Their limited daily mobility makes it difficult for them to lower their exposures to high pollution levels, as found in X. Ma et al. (2020). In this light, these socially disadvantaged groups call for particular attention in public policies.

Although this study advances our understanding of the NEAP, several caveats and qualifications are in order. First, the NEAP largely operates for mobility-dependent exposures. It might not affect exposures to environmental factors that operate largely in or around people's home neighborhoods (e.g., collective efficacy or social capital). Second, the NEAP does not operate and thus is not relevant to people with very low daily mobility. Third, the NEAP does not operate when there is little or no spatiotemporal variation in the environmental factor being examined. For example, sulfate level tends to vary slightly over space at the metropolitan scale (i.e., 100 km; Gilliland et al. 2005). In other words, MIE to sulfate would be similar to RIE to sulfate even if people move to different nonresidential neighborhoods in their daily lives and, as a result, they might not experience a strong degree of neighborhood effect averaging. Finally, it is unclear whether the frequency distributions of all mobility-dependent exposures would follow a bell-shaped curve, although several recent studies, including this one, observed it (e.g., Dewulf et al. 2016; J. Kim and Kwan 2019; Yu, Russell, Mulholland, and Huang 2018). When the frequency distribution of individual exposures is not a bell-shaped distribution, it is less certain whether neighborhood effect averaging would operate as suggested by the NEAP.

Further, this research has several limitations that future studies need to address. First, due to data limitations, we assumed that ozone level is homogeneous within 1 km^2 resolution and could not estimate the air pollution levels in different microenvironments (e.g., indoors) or consider different inhalation rates associated with different travel modes (e.g., driving, walking, and biking) and people's age. Recent studies have shown that these are also important factors that affect individual exposures to air pollution (e.g., Gulliver and Briggs 2005; Dons et al. 2011; Lu and Fang 2015; J. Ma et al. 2020). Furthermore, there is an issue of the temporal mismatch between the day when the hourly ground-level ozone surfaces are modeled (15 August 2018) and the day when individuals' activity-travel diary data were reported (2017). This mismatch could introduce uncertainties regarding people's exposure to ozone because people's daily mobility might vary over the time or season of the year (Axhausen et al. 2002). Activity-travel survey data from 2017 that reflect people's routine daily activities and trips in general, however, can still be used with 2018 ozone data for a methodological investigation that compares residence-based and mobility-based individual exposures to ozone.

Second, although this study assumed that participants used the routes with the shortest travel time to travel between activity locations, they might not actually do so in real-world situations (Zhu and Levinson 2015; Tang and Levinson 2018; Park and Akar 2019). The methods used in this study based on more widely available data (i.e., activity-travel data), however, would allow many researchers to study the NEAP, and recent studies indicate that the results obtained with this approach are consistent with those obtained with Global Positioning System (GPS) tracking and sensing data (e.g., compare Park and Kwan [2017] and J. Ma et al. [2020]). Future studies would, of course, benefit from using real-time GPS tracking, mobile sensing, and accelerometers (e.g., Houston, Luong, and Boarnet 2014;

Lee and Kwan 2018; J. Ma et al. 2020) to more accurately capture human mobility and exposures to microenvironments in space and time.

Third, this study considered only weekday trips when estimating individual ozone exposures. It is widely known, though, that people's activity-travel patterns between weekdays and weekend days could be different because people tend to make more discretionary trips than mandatory trips (e.g., commute trips) on weekend days (Federal Highway Administration 2018). Moreover, overlooking weekend trips might not capture the daily mobility patterns of certain social groups (e.g., low-income workers in the retail sector) because they still need to work during the weekend, which might lead to higher daily mobility and in turn a higher neighborhood effect averaging. Future studies on the NEAP should thus also consider weekend trips because the different activity-travel patterns between weekdays and weekend days could be associated with different levels of neighborhood effect averaging.

Finally, other types of mobility-dependent exposures in addition to air pollution should also be examined to enrich understanding of the NEAP. Past studies on neighborhood effects have examined individual exposures to many mobility-dependent environmental factors (e.g., noise pollution, traffic congestion, healthy food environments, and green spaces). Neighborhood effect averaging might manifest differently for different environmental factors because of their specific spatiotemporal dynamics and complex interactions with human mobility. For example, healthy food environments could vary considerably over space and time because of limited opening hours of food outlets and changes in traffic conditions over the course of a day (Widener and Shannon 2014; Chen and Kwan 2015; Widener et al. 2017; Wang and Kwan 2018). It is thus important to undertake further studies to investigate the NEAP with a focus on people's mobility-dependent exposures to various environmental factors.

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