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Assessment of Inter-Individual, Geographic, and Seasonal Variability in Estimated Human Exposure to Fine Particles

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Abstract

Health effects associated with ambient fine particle ($PM_{2.5}$) exposure are typically estimated based on concentration-response (C-R) functions using area-wide concentration as an exposure surrogate. Persons 65 and older are particularly susceptible to adverse effects from $PM_{2.5}$ exposure. Using a stochastic microenvironmental simulation model, distributions of daily $PM_{2.5}$ exposures were estimated based on ambient concentration, air exchange rate, penetration factor, deposition rate, indoor emission sources, census data, and activity diary data, and compared for selected regions and seasons. Even though the selected subpopulation spends an average of over 20 hours per day indoors, the ratio of daily average estimated exposure to ambient concentration (E_a/C) is approximately 0.5. The daily average E_a/C ratio varies by a factor of 4 to 5 over a 95% frequency range among individuals, primarily from variability in air exchange rates. The mean E_a/C varies by 6 to 36% among selected NC, TX and NYC domains, and 15 to 34% among four seasons, as a result of regional differences in housing stock and seasonal differences in air exchange rates. Variability in E_a/C is a key factor that may help explain heterogeneity in C-R functions across cities and seasons. Priorities for improving exposure estimates are discussed.

Keywords

$PM_{2.5}$; exposure; modeling; variability

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SUPPORTING INFORMATION AVAILABLE

Additional information on background motivation of assessing $PM_{2.5}$ E_a/C ratio; justifications for inputs (ACH, P, k) selection; inter- and intra-individual variability in non-ambient exposure (E_{na}) and total exposure (E_t); discussion of seasonal variability in elderly activity patterns; discussion of autocorrelation in elderly activity patterns; discussion of potential modeling assumptions that may cause decreased variability in the exposure results; discussion of the difference in mean E_a/C ratios; other SHEDS-PM input parameters for microenvironmental $PM_{2.5}$ concentrations (Table S1), excluding residential microenvironment; summary of 2002 average daily ambient $PM_{2.5}$ concentrations to the SHEDS-PM model input (Table S2); summary of inter- and intra-individual coefficient of variations (CVs) for NC Domain, Spring 2002 (Table S3); paragraphs and tables about correlations of total Exposure (E_t) by day type for NC domain, Spring 2002 (p.SI-9, p.SI-10, Table S4), and summary of average ratio of ambient exposure to ambient concentration (E_a/C) and non-ambient exposure (E_{na}) by day type for all cases (Table S5); correlations coefficients between daily average exposures and concentrations (Table S6); comparison of distribution of elderly activity based on time for males and females in winter and summer (Mean ± 95% Confidence Interval) (Table S7); cumulative distribution functions (CDFs) of the geographic and seasonal variability in the daily total exposure (E_t), non-ambient exposure (E_{na}), and ambient exposure (E_a) in NC domain, Harris County, and NYC in 2002 (Figure S1 – Figure S3); CDFs of the geographic and seasonal variability in the monthly average ratio of ambient exposure to ambient concentration (E_a/C) in NC domain, Harris County, and NYC in 2002 (Figure S4); and distributions of inter-individual (Figure S5) and intra-individual (Figure S6) coefficient of variations (CVs) of total exposure (E_t) for NC domain, Spring, 2002. This information is available free of charge via the Internet at http://pubs.acs.org/.

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1. INTRODUCTION

According to the U.S. Environmental Protection Agency (EPA) Integrated Science Assessment (ISA) for Particulate Matter, a causal or likely to be causal relationship exists between short-term (daily) human exposure to fine particulate matter ($PM_{2.5}$) and several health effects, such as mortality, cardiovascular and respiratory morbidity.[1] Children and adults 65 years and older are the two most susceptible subpopulations.[1] The proportion of older adults in the US population will increase from 13% in 2011 to 20% in 2030.[2] Thus, PM-related health incidents could occur more frequently in the future.

$PM_{2.5}$ ambient concentration is frequently used in epidemiological studies as a surrogate for personal exposure to ambient $PM_{2.5}$.[1] However, actual exposure depends on the amount of time an individual spends in different microenvironments, which are surroundings that can be treated as homogeneous or well characterized in the concentrations of an agent.[3] Microenvironments include various indoor locations (e.g. home, work, school, restaurants, stores), outdoors, in transit, and others.[4] On average, people spend more than 80 percent of daily time indoors and two thirds of daily time at home.[5] For indoor microenvironments, a portion of ambient $PM_{2.5}$ penetrates indoors, and some deposits to interior surfaces.[4] For some cases, the individual indoor $PM_{2.5}$ concentrations could be higher than ambient because of particle re-suspension resulting from human activity.[6] However, SHEDS-PM does not model re-suspension. On average for a population, the daily exposure to particles of ambient origin is typically less than the ambient concentration, and the difference contributes to exposure error.[7,8] Using ambient $PM_{2.5}$ concentrations as a surrogate for the community average personal exposure to ambient $PM_{2.5}$ will bias the estimation of health risk coefficients by the ratio of ambient $PM_{2.5}$ exposure to ambient $PM_{2.5}$ concentration (E_a/C).[1]

Findings from $PM_{2.5}$ exposure panel studies indicate substantial variability in 24-h average personal $PM_{2.5}$ exposures among US regions.[9–12] Individuals are exposed to $PM_{2.5}$ of both ambient and nonambient origin, and both sources of $PM_{2.5}$ may contribute to adverse health outcomes. Total and nonambient PM exposure are poorly correlated with ambient PM concentration.[13] Ambient PM concentrations are affected by meteorology and by changes in emission rates and locations of emission sources, whereas nonambient PM concentrations are influenced by daily activities of people. The E_a/C ratio depends on housing type and activity patterns, air exchange rate, and PM deposition rate. It varies between 0 and 1 among individuals, and varies among cities and seasons.[14] Since concentration-response functions are typically heterogeneous across cities and seasons, characterizing the factors that influence E_a/C could be useful in correcting for exposure error.

Inter-individual variability in exposure may also be influenced by the sampling time interval. Many time-series studies examine the associations of short-term health outcomes based on a 24-hr interval.[15] There is some evidence, based on analysis of PM_{10} data, that mortality or morbidity on a given day is influenced by prior PM exposures up to more than a month before the date of death.[16] Thus, averaging times other than 24-hr averages should be considered to provide appropriate modeling results for sub-acute or chronic health effects applications.[17] Therefore, quantification of the sensitivity of inter-individual variability in exposure with respect to different averaging times may help to better inform health effects studies.

$PM_{2.5}$ exposure can be estimated based on field study or simulation models. Measured exposure data mainly come from either a few multi-city probability-based field studies, such as the Relationship between Indoor, Outdoor and Personal Air (RIOPA) study[11], the Detroit Exposure Aerosol Research Study (DEARS)[18], and the Canadian Windsor Ontario Exposure

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Assessment Study (WOEAS)[19], or longitudinal panel studies focused on small numbers of exposed individuals in susceptible subpopulations, such as the elderly.[20]

Field studies are time-consuming and expensive to conduct, which limits their sample sizes. As a result, measurements may only represent participants in that study and may not necessarily be generalizable. In comparison, a scenario-based exposure model can be an alternative tool for quantifying human exposure on a population basis.[21] For example, the U.S. Environmental Protection Agency has developed the Stochastic Human Exposure and Dose Simulation model for Particulate Matter (SHEDS-PM). SHEDS-PM is used here for simulating exposure because it has undergone several evaluation and validation studies.[22–25]

As summarized by Sarnat et al.[14], several measurement studies have been conducted to estimate the associations between $PM_{2.5}$ personal ambient exposure and ambient concentration, which can be used to estimate the E_a/C ratio. Although there have been studies that quantified geographic and seasonal variability in the E_a/C ratio for other pollutants, such as ozone[26], CO[27], and SO_2[28], there has not been systematic quantification of variation in for $PM_{2.5}$ using a consistent framework. E_a/C ratios differ substantially among pollutants depending on chemical reactivity, solubility, and pollutant lifetime. The average E_a/C ratios for highly reactive ozone are typically 0.1 to 0.3, for relatively unreactive CO are around 1, and for highly soluble SO_2 are from 0.08 to 0.13. In contrast, the E_a/C ratio for $PM_{2.5}$ depends on factors such as interception and impaction that affect penetration from outdoors to indoors, and indoor deposition rate.[1]

The objectives of this paper are to: (1) assess the sensitivity of inter-individual variability in exposures with respect to averaging time; (2) evaluate geographic differences in inter-individual variability in exposures; and (3) evaluate seasonal differences in inter-individual variability in exposures.

2. METHODOLOGY

The methodology includes: (1) scenario-based exposure modeling; (2) study design and identification of data sources for the case study; and (3) analysis of exposure model output.

2.1. Scenario-based Exposure Modeling

Burke et al.[21] evaluated SHEDS-PM using measurement data from a PM panel study conducted in the Research Triangle Park, NC area. The model predictions of individual and population exposures to $PM_{2.5}$ are generally consistent with the estimates derived from the personal measurement data. Other studies have reviewed the algorithms and input data for SHEDS-PM, and recommended improvements are incorporated here. Cao and Frey reviewed default Environmental Tobacco Smoke (ETS) related inputs and recommended updates to input data for the proportion of smokers and other smokers, and for cigarette emission rates.[22] Liu et al. reviewed the algorithms and default inputs for the in-vehicle microenvironment, and proposed an alternative approach which integrates a dispersion model and a mass balance approach.[23] Cao and Frey recommended updates to the distributions of ACH, P, and k for selected areas and seasons.[24]

Estimates of inter-individual variability in outdoor and indoor microenvironmental $PM_{2.5}$ exposures for a simulated population are based on user-supplied ambient air quality data, model-incorporated census data, and human activity data for the selected geographic domain.[25] Individuals are randomly generated from the year 2000 US Census to represent the population in a selected area. For each simulated individual, the amount of time spent in each microenvironment is derived from the Consolidated Human Activity Database (CHAD).[29] Algorithms are applied to estimate $PM_{2.5}$ concentrations in each

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microenvironment based on ambient concentration and indoor sources. Simulated microenvironments include outdoors, home, office, school, store, restaurant, bar and vehicle.

For the residential microenvironment, SHEDS-PM utilizes a single-compartment, steady state mass balance equation to calculate residential $PM_{2.5}$ concentration.[25] The contribution from indoor emission sources such as smoking, cooking, cleaning and other sources is quantified. The housing type categories in SHEDS-PM are single-family detached, single-family attached, multiple family, mobile home and other. Based on the US Census 2000 Housing Survey, lognormal distributions are used for each housing type in SHEDS-PM to represent inter-home variability in indoor volume. The key mass balance inputs include ACH, P and k. ACH is the volume flow of air within the indoor microenvironment divided by the interior volume. It is affected by air leakage through cracks and crevices in the building envelope, natural ventilation through open windows and doors, and mechanical ventilation by fans.[30] Mechanical ventilation would lower indoor ambient PM exposure because a substantial portion of indoor air is recirculated and, consequently, ACH is smaller. Distributions of ACH by area and season reflect the variability in ACH caused by different ventilation practices used and housing types/volumes of each individual. P is the portion of particles that pass through the building from outdoors. Deposition rate, k, is the settling of airborne particles onto indoor surfaces.[11]

2.2. Study Design

The focus here is to quantify possible regional and seasonal variability in estimated exposure. Adults over 65 years old are selected because they are a susceptible subpopulation with respect to $PM_{2.5}$ exposure.[1] To address regional differences, three urban areas are chosen to represent diverse southeast, south central and northeast US climate zones. These areas include: (1) a six-county area in North Carolina along Interstate 40, comprised of Wake, Durham, Orange, Alamance, Guilford, and Forsyth Counties, that includes the cities of Raleigh, Durham, Burlington, Greensboro, High Point, and Winston-Salem; (2) Harris County in Texas, including the city of Houston; and (3) New York City, including Bronx, New York, Kings, Queens, and Richmond Counties. Approximately 50,000 individuals 65 years and older are simulated from all census tracts of each area for a period of 30 days in each season. To address seasonal differences, one month from each of four seasons is selected, including April for spring; July for summer; October for fall; and December for winter. SHEDS-PM model version 3.7 was used to run all cases. Typically it takes approximately 5 to 6 hours of CPU time to simulate exposures for 50,000 individuals for a 30-day time period.

Daily average $PM_{2.5}$ air quality data are obtained from U.S. EPA based on predictions of 2002 average concentrations for 12 km by 12 km grid cells from the Community Multiscale Air Quality (CMAQ) model, which were updated with available monitoring data using Bayesian statistical inference.[31] Demographic distributions by age, gender and housing type are sampled from year 2000 US Census data. CHAD diary data are matched to each simulated individual based on gender, age, day type, and smoking status. ETS is modeled in residential, restaurant, and bar microenvironments. The proportions of smokers and non-smokers are estimated based on region-specific 2002 data.[32–35] Input parameters for residential microenvironments, such as ACH, P, k, and cigarette emission rate, and for the in-vehicle microenvironment, are specified based on related literature. [22–24,30,36–38] Parameters of other microenvironments are based on Burke *et al.*[20]

2.3. Statistical Analysis Methods

SHEDS-PM outputs are processed and analyzed using Predictive Analytics SoftWare (PASW) 18.0. The SHEDS-PM model quantifies time spent by each simulated individual in

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different microenvironments and the corresponding microenvironmental $PM_{2.5}$ concentrations, and estimates daily average E_a, E_{na}, and E_t for each simulated individual. The E_a/C ratio is calculated for each simulated individual for each simulated day.

Variability in exposure among individuals on a given day is compared to variability for a single individual over time to assess the relative importance of inter- versus intra-individual variability. The variability among individuals and over time is quantified based on coefficients of variation (CV). The NC domain spring case is selected as an example. The reported CV of inter-individual variability is an average of daily CVs of inter-individual variability over simulated days. The reported CV of intra-individual variability is an average of individual CVs of intra-individual variability in exposure over simulated individuals.

To examine the sensitivity of inter-individual variability with respect to averaging time, the daily E_a/C ratio is further averaged by individual over one month to represent a longer term. Both daily and monthly ratios of E_a/C are compared for each geographic area and season. The analysis included comparisons of 95% frequency ranges inferred from simulated cumulative distribution functions (CDFs) of inter-individual variability in exposure, and comparisons of the effect of longitudinal versus randomized day-to-day sampling of activity dairies on the distribution of monthly average exposures. Individual daily exposure values are extracted from SHEDS-PM output to construct a 50,000 individual by 30 day exposure matrix. For each day, correlations of inter-individual variability in exposure are calculated with each other day. Days are categorized by day type, including weekday, Saturday and Sunday. For each of the 30 days, the average correlation with all other days of the same type, and with all days of each of the other two types, are estimated.

To assess the geographic and seasonal differences in inter-individual variability in exposures, daily ratios of E_a/C, E_{na} and E_t are compared among geographic areas for the same season and among multiple seasons for the same area.

3. RESULTS

3.1. Key Inputs

This section assesses SHEDS-PM inputs that affect inter-individual variability in exposure. The average daily ambient $PM_{2.5}$ concentrations were highest in July compared to the other months for all regions.

Values of ACH, P, and k for the residential microenvironment are shown in Table 1. Distributions of variability in ACH by geographic region are based on the Relationship of Indoor, Outdoor and Personal Air (RIOPA) study[11] from 1999 to 2001, Murray and Burmaster,[36] Koontz and Rector,[37] and Wallace et al.[38] Distributions of variability in P and k are based on the PTEAM[30] and RIOPA[11] studies. The distribution types are selected based on Cao and Frey[24] and are explained in the Supporting Information. Sensitivity analysis by Cao and Frey assessed the effects of ACH, P and k on estimated human exposures.[24] ACH is the most sensitive input for both ambient and non-ambient exposure to $PM_{2.5}$, whereas the results are not sensitive to the choice of distribution for P and k.

Table 2 shows other input factors that affect inter-individual exposure variability, such as demographics, smoking prevalence, housing types, and human activity patterns. Females account for approximately 60 percent of the total elderly population in each area. Exposure to indoor sources of $PM_{2.5}$ is typically higher as the housing interior volume decreases.[25] The population weighted average time spent in different microenvironments differs by gender.

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3.2. Output

Inter-individual variability in estimated exposure to $PM_{2.5}$ is compared with respect to averaging time, area, and season.

3.2.1. Averaging Time—Inter- and intra-individual variability in exposure are compared based on the CV of inter- and intra-individual variability in daily exposure, respectively, as detailed in Table S3 of the Supporting Information. Inter-individual variability results in part from spatial variation in ambient concentration. However, inter-individual variability is also influenced by other factors such as ACH and activity. For the NC spring case, on average, CVs of inter- and intra-individual variability in daily average C are 0.11 and 0.32, respectively. Thus, C varies relatively little over space and among exposed individuals on a given day, and varies more substantially with time from day-to-day, which is consistent with other studies that are summarized in the PM ISA.[1] However, inter-individual variability in exposure is influenced by variability in other factors in addition to C. The CV of inter-individual variability in E_a is 0.37, which is much larger than that for C. The CV of intra-individual variability in E_a is 0.45, which is 18% higher than for inter-individual variability. Thus, exposure varies more over time than it does between individuals on a given day. The CV of E_a/C is similar (about 0.3) for both inter- and intra-individual variability, indicating that factors influencing E_a other than C, such as ACH, P, and k have similar variability among individuals or over time.

Inter-individual variability in estimated exposure varies with respect to averaging time. When comparing daily and monthly average distributions of inter-individual variability in estimated E_a/C for each geographic area and season, they have the same mean as expected, but the standard deviation of the daily average E_a/C is approximately twice that of the monthly average. The 95% frequency interval for the daily average E_a/C ratio typically ranges from 0.2 to 0.9, whereas the range for the monthly average is approximately 0.3 to 0.7, as shown in Figure 1 for the NC domain in spring. The variation in E_a/C is reduced as the averaging time increases, since day-today variations are averaged out for each individual. For the NC spring case, the correlations of inter-individual variability in daily E_a/C among days of the same day type are around 0.4, whereas there is little correlation among days of different day types.

The range of the distribution of monthly average E_a/C is influenced in part by the method used in SHEDS-PM for longitudinal sampling of activity diaries. To explore how sensitive the results are to this sampling method, an alternative NC spring case was analyzed in which individuals were randomly sorted from day-to-day, thus leading to no significant correlation in day-to-day comparisons of inter-individual variability. Because the longitudinal simulation is based on positive correlations from day-to-day, it is expected to provide a wider range of monthly average inter-individual variability than a randomized simulation. The difference in results between the two cases indicates whether longitudinal simulation has a significant effect. For the randomized case, the 95% frequency range in inter-individual variability of monthly average E_a/C is from 0.43 to 0.55, which is about one-third the range of the longitudinal case. Thus, the results are sensitive to the approach used for longitudinal simulation.

3.2.2. Geographic Variability—Inter-individual variability in exposure differs among climate zones. Figure 2 presents the CDFs of the estimated daily average E_a/C for each area and season. Although the range is similar among areas considered, the mean values differ. As indicated in Table 3, the simulated elderly adults are exposed to approximately half of the modeled ambient $PM_{2.5}$ concentrations. The highest and the lowest mean E_a/C among geographic areas for a given season differ by 6% to 16% except in fall, which has a larger

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difference of 36%. The geographic differences in the mean E_a/C ratio are associated with differences in ACH. Lower ACH leads to less penetration of ambient $PM_{2.5}$, which results in lower indoor ambient exposure to $PM_{2.5}$. Therefore, areas with lower ACH typically have lower E_a/C ratios. For example, Harris County, TX has more air conditioning usage in the summer[39], which leads to lower air exchange and consequently lower E_a/C ratio than NC and NYC.

The average E_{na} for the simulated population differs among areas, as shown in Table 3. The differences in the mean values among regions for a given season vary from 11% to 55% for the total population. The major factors that contribute to the geographic variability in estimated E_{na} are smoking prevalence, indoor volume, and ACH. A higher proportion of smokers leads to higher non-ambient $PM_{2.5}$ emissions. Smaller indoor volume leads to less dilution of indoor $PM_{2.5}$ sources. Lower ACH results in longer retention of indoor emissions. Generally, E_{na} is most sensitive to ACH. Areas with lower ACH tend to have higher average E_{na}. However, the combined effect of lower smoking prevalence and higher indoor housing volume sometimes can be more influential than ACH, as illustrated by the TX domain in summer. This domain has the smallest proportion of smokers and largest average indoor volume. Although the summer ACH is much less for the TX versus NC or NYC domains, the population average E_{na} for the TX domain is the lowest.

The daily average E_t varies by 10% to 28% among geographic areas for any given season for the total population. However, non-smokers not exposed to ETS have much lower average E_t than persons with ETS exposure. For people with ETS exposure, approximately 85% of daily E_t is non-ambient. Thus for those with ETS exposure, the average E_t is highly influenced by the non-ambient exposure level. This is because the upper-tail values of E_{na} (above the 90th percentile) are usually 2 to 10 times higher than for E_a.

3.2.4. Seasonal Variability—In the same region, the average daily E_a/C ratio differs among seasons by 16% in the NC domain and by 34% in NYC, as shown in Table 3. Many dwellings in NYC are not air conditioned, and residents tend to open windows more in the summer. In contrast, in Harris County, the average E_a/C is 15% lower in summer than in the fall. For the NC domain, the E_a/C ratios are similar between summer and fall. The seasonal difference in the E_a/C ratio is partly associated with more widespread air conditioner use in TX and NC.[39]

Mean values of E_{na} vary by 21% to 37% by region among seasons. Because several factors affecting the average estimated daily E_{na} are similar within a region, such as smoking prevalence, indoor volume, demographics, and individual activity patterns, seasonal differences in E_{na} are most sensitive to seasonal differences in ACH.

The seasonal variability in estimated average daily E_t is not as pronounced compared to geographic variability. The difference in the average daily E_t among seasons for a given region ranges from 15% to 19%, which is mainly attributed to seasonal variations in ACH. For people exposed to ETS, because E_t is dominated by the contribution of non-ambient exposure, higher ACH leads to lower E_t. But for non-smokers, E_{na} only accounts for about 40% in their daily E_t on average. Therefore, higher ACH leads to higher E_t for non-smokers.

4. DISCUSSION

As expected, the ambient air quality data in grid cells used as input to the SHEDS-PM model typically exhibited rather low spatial variation within a geographic domain on each day, with CV < 0.2 for 11 of the 12 area and season cases studied. Daily average ambient exposures are significantly lower than ambient concentrations and vary by season and

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location. Furthermore, there is substantial inter-individual variability in exposure that is not explained by ambient concentration alone.

A limitation not readily addressed by CHAD is the possible seasonal differences in activity patterns. Based on analysis of CHAD, as detailed on page SI-10 and Table S7 of the Supporting Information, differences in the time spent indoors or time spent outdoors are found to be statistically significant depending on the gender, region, and season. However, these results are based on aggregation of CHAD data across large geographic regions that represent generic climate zones. There is insufficient data in CHAD from which to quantify differences in activity pattern by gender, region, and season for the specific geographic areas that are the focus here. Clearly, there is a need to further develop CHAD to contain diaries representative of geographic areas and seasons of interest, and to refine the exposure model to take ambient conditions into account when sampling diaries.

The CV in time spent outdoors among individuals was found to be similar to the CV for 11 individuals for whom more than 4 days of diaries were available in CHAD. Thus, the limited evidence suggests that activity patterns are repeatable from day-to-day and similar among individuals, at least for the selected subpopulation. The simulation model appropriately accounts for similarity in day-to-day activity.

Non-ambient exposure to $PM_{2.5}$ is approximately uncorrelated with ambient concentration (average $r_p = -0.002$, as detailed in Table S6 of the Supporting Information), which is consistent with other studies that are summarized by EPA[1]. Average levels of E_{na} vary by area and season mainly because of differences in ACH. For people exposed to ETS, E_{na} is the dominant contributor to E_t.

The E_a/C ratio varies by individual, geographic area, season, and spatial-temporal averaging times. Therefore, quantification of the E_a/C ratio has implications for air pollutant exposure assessment, risk management, and epidemiologic studies. The daily E_a/C ratio differs by a factor of 4 to 5 over a 95% frequency range among individuals, indicating that some people are very highly exposed compared to others because of factors other than ambient concentration. The E_a/C ratio varies among individuals because of differences in activity patterns, housing characteristics, and seasons. The day-to-day variation of estimated individual daily average E_a is highly correlated ($r_p > 0.8$) with that of C. Even though biased, the use of ambient concentration as a surrogate for ambient exposure in epidemiology studies may still account for temporal trends in exposure.

The distribution of E_a/C ratios in each area and season implies that, in general, exposure to ambient $PM_{2.5}$ is less than the ambient concentration. On average, exposures to simulated individuals are approximately half of the ambient concentrations. These findings indicate that concentration-response functions developed in epidemiological studies using ambient concentration as surrogate for exposure are biased when compared to exposure concentration.

Exposure, and not just concentration, should be considered in developing risk management strategies to reduce uncertainty in health effect estimates, and to identify highly exposed groups and possible exposure reduction strategies. High-end daily average ambient exposures among individuals are influenced by factors other than high ambient concentration, such as ACH by location and season. ACH is related to housing type and ventilation practices used. E_a/C is well correlated (r_p=0.5 to 0.6) with ACH, but has little correlation with ambient concentration C. Thus the distribution of inter-individual variability in the E_a/C ratio can be used to identify the need for providing advisory information to the public. Such information might include, for example, advice to reduce ventilation with outside air on high ambient $PM_{2.5}$ days.

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The average E_a/C ratio illustrates the potential exposure error related to epidemiologic estimates of concentration-response (C-R) ratios. Regional or seasonal differences in the average E_a/C ratio may help to explain variations in concentration-response relationships between cities and seasons, because the estimated health effect parameter is a function of the E_a/C ratio. The range in mean E_a/C among studied areas and seasons is from 0.44 to 0.60. The difference between these ratios is statistically significant based on the simulated results and represents a 36 percent relative difference. Because $E_a/C \geq 0$ and typically $E_a/C < 1$ for most individuals, the population mean of E_a/C is constrained and therefore the range of possible difference in average E_a/C ratio is also constrained. Region and season-specific E_a/C ratios are recommended as a factor to consider when interpreting heterogeneity in epidemiologic studies.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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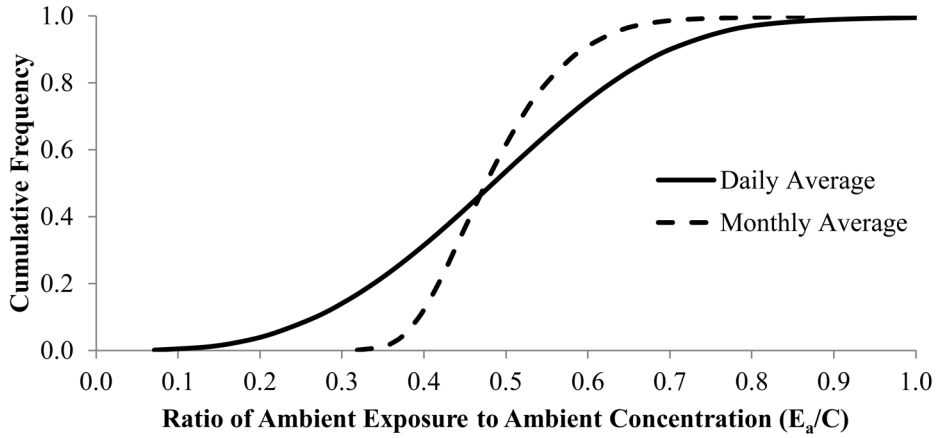

Figure 1.

Comparison of Inter-Individual Variability in the Ratio of Estimated Ambient Exposure to Ambient Concentration (E_a/C) for Selected Averaging Times, NC domain, Spring 2002

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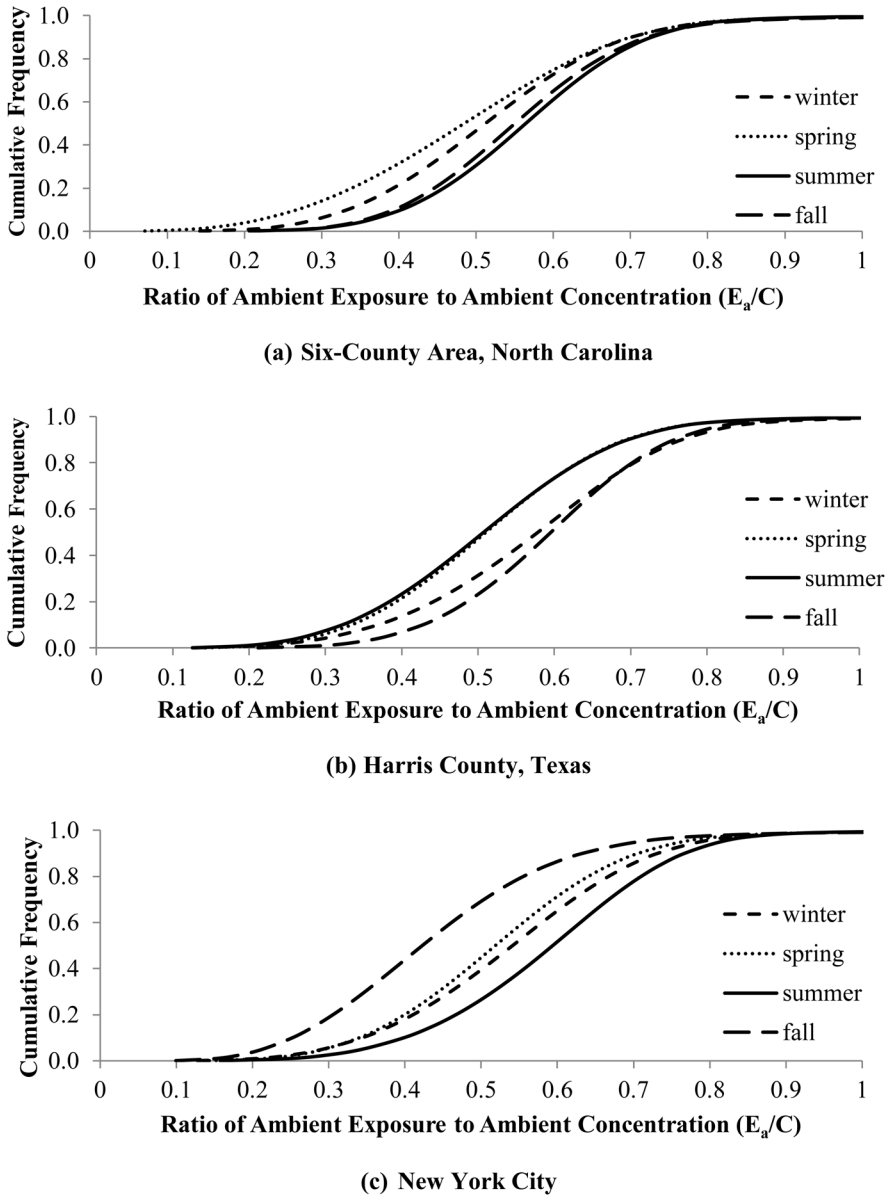

Figure 2.

Geographic and Seasonal Variability in the Ratio of Estimated Daily Ambient Exposure to Ambient Concentration for the NC domain, Harris County, and NYC, 2002

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Table 1

Residential Microenvironment Input Parameters

Parameter	Distribution Type [a]	Location [b]	Season	Value [c]
Penetration (P)	Triangular	ALL	ALL	Min= 0.70, Mode= 0.78, Max= 1.0
Deposition (k)	Normal	ALL	ALL	$\mu = 0.40\ h^{-1}$, $\sigma = 0.01\ h^{-1}$
Air Exchange Rate (ACH)	Lognormal	NC domain	Winter	$\mu_g = 0.38\ h^{-1}$, $\sigma_g = 1.80\ h^{-1}$
			Spring	$\mu_g = 0.31\ h^{-1}$, $\sigma_g = 2.31\ h^{-1}$
			Summer	$\mu_g = 0.54\ h^{-1}$, $\sigma_g = 1.70\ h^{-1}$
			Fall	$\mu_g = 0.49\ h^{-1}$, $\sigma_g = 1.62\ h^{-1}$
		Harris County, TX	Winter	$\mu_g = 0.56\ h^{-1}$, $\sigma_g = 2.20\ h^{-1}$
			Spring	$\mu_g = 0.38\ h^{-1}$, $\sigma_g = 1.80\ h^{-1}$
			Summer	$\mu_g = 0.37\ h^{-1}$, $\sigma_g = 1.90\ h^{-1}$
			Fall	$\mu_g = 0.65\ h^{-1}$, $\sigma_g = 1.80\ h^{-1}$
		NYC	Winter	$\mu_g = 0.45\ h^{-1}$, $\sigma_g = 2.03\ h^{-1}$
			Spring	$\mu_g = 0.40\ h^{-1}$, $\sigma_g = 1.82\ h^{-1}$
			Summer	$\mu_g = 0.64\ h^{-1}$, $\sigma_g = 2.09\ h^{-1}$
			Fall	$\mu_g = 0.22\ h^{-1}$, $\sigma_g = 1.72\ h^{-1}$

[a]Triangular distribution parameters are the minimum, mode, and maximum; normal distribution parameters are the mean μ and standard deviation σ; lognormal distribution parameters are the geometric mean μ_g and standard deviation σ_g. The selection of distribution types are based on Cao and Frey (2011) and is described in the Supporting Information.

[b]NC includes Wake, Durham, Orange, Alamance, Guilford, and Forsyth Counties; TX includes Harris County; NYC includes Bronx, New York, Kings, Queens, and Richmond Counties.

[c]Sources: Cao and Frey (2011); P, k: Weisel et al. (2005), Özkaynak et al. (1996); ACH: NC- Murray and Burmaster (1995), Wallace et al. (2006); TX- Murray and Burmaster (1995), Weisel et al. (2005) ; NYC- Murray and Burmaster (1995), Koontz and rector (1995).

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Table 2

Exposure Model Demographic Input Data Regarding Population Distribution, Smoking Prevalence, Housing Types, and Activity Patterns

Distribution of Population by Age and Gender [a] (%)

Age Group	Six-County Region, NC		Harris County, TX		New York City	
	Male	Female	Male	Female	Male	Female
65–69	12.8	15.5	14.3	17.0	12.0	15.7
70–74	10.9	14.9	11.5	15.0	10.2	14.9
75–79	8.2	12.7	8.3	12.1	7.8	12.8
80–84	4.5	8.9	4.2	7.6	4.7	9.0
85–89	2.1	5.6	2.0	4.7	2.5	5.8
90–94	0.6	2.5	0.6	2.0	0.9	2.6
≥95	0.2	0.8	0.2	0.6	0.3	0.9
Total	39.2	60.8	41.4	58.9	38.4	61.6

Distribution of Smoking Prevalence in Older Adults by Gender [b] (%)

	Six County Region, NC		Harris County, TX		New York City	
Age Group	Male	Female	Male	Female	Male	Female
≥65	18.5	10.5	12.0	4.6	9.3	10.4

Distribution of Housing Types [c] (%)

	Six County Region, NC	Harris County, TX	New York City
Single Family Detached	58.8	62.2	13.2
Single Family Attached	4.6	4.6	9.9
Multiple Family	31.3	29.6	76.8
Mobile Home	5.3	3.5	0.1

Distribution of Older Adult Daily Activity Patterns by Gender [d] (hr/day)

	Time Spent Outdoors		Time Spent Indoor		Time Spent in Vehicle	
Age	Male	Female	Male	Female	Male	Female
≥65	2.1	0.8	20.7	22.3	1.2	0.9

[a] Source: U.S. Census 2000.

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[b] Sources: NC and TX – Behavioral Risk Factor Surveillance System (BRFSS), 2002; NYC – Epiquery, 2002.

[c] Source: U.S. Census 2000 – Housing Survey. Average indoor volume: single family detached: 466 m^3; single family attached: 371 m^3; multiple family: 241 m^3; mobile home: 222 m^3.

[d] Source: Consolidated Human Activity Database (CHAD) (McCurdy et al., 2005). Outdoor includes street, parking lot, gas station, park, playgrounds, pool, farm, and all other outdoor microenvironments; indoor includes home, office, school, store, bar, restaurant, and all other indoor microenvironments; in vehicle includes travel by car, truck, motorcycle, bus, train, subway, airplane, boat, walking, bicycle, and waiting for travel either indoor or outdoor.

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Table 3

Geographic and Seasonal Variability in Exposure [a]

Area[b]	Season	E_a/C[c]		E_a[c] (μg/m³)		E_{na}[c] (μg/m³)		E_t[c] (μg/m³)	
		Mean	StdDev	Mean	StdDev	Mean	StdDev	Mean	StdDev
NC domain	winter	0.52	0.15	6.2	3.7	12.9	29.3	19.1	29.4
	spring	0.49	0.17	6.2	3.0	13.9	32.2	20.1	32.1
	summer	0.57	0.13	11.7	6.3	11.0	24.9	22.6	25.5
	fall	0.56	0.14	7.6	4.5	11.5	26.0	19.1	26.3
Harris County, TX	winter	0.58	0.16	6.2	3.3	8.6	21.4	14.8	21.5
	spring	0.51	0.14	8.0	3.8	10.2	25.7	18.2	25.8
	summer	0.51	0.15	8.0	3.8	10.0	24.2	18.0	24.4
	fall	0.60	0.13	8.0	3.5	8.0	19.3	16.0	19.5
NYC	winter	0.54	0.15	7.1	3.9	13.0	31.2	20.1	31.2
	spring	0.52	0.15	6.2	4.3	13.7	31.8	20.0	32.0
	summer	0.59	0.15	12.2	8.5	11.2	27.3	23.4	28.2
	fall	0.44	0.17	4.6	3.3	17.7	41.5	22.3	41.6

[a] Mean and standard deviation are based on individual daily average exposures obtained using the Stochastic Human Exposure and Dose Simulation for Particulate Matter (SHEDS-PM).

[b] NC includes Wake, Durham, Orange, Alamance, Guilford, and Forsyth Counties; TX includes Harris County; NYC includes Bronx, New York, Kings, Queens, and Richmond Counties.

[c] E_a/C: ratio of ambient exposure to ambient concentration; E_a: ambient exposure (μg/m³); E_{na}: non-ambient exposure (μg/m³); E_t: total exposure (μg/m³).