Personal $PM_{2.5}$ Exposure during Pregnancy in an Environmental Health Disparities Population

by

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Dedication

This dissertation is dedicated to my family, especially my father and my brother, for their unconditional support, as well as my friends for their company along the journey.

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Abbreviations

APEX	Air Pollutants EXposure (model)
AQS	Air Quality System
BIC	Bayesian Information Criterion
BMI	Body Mass Index
CA	California
CALINE	California Line Source Dispersion Model
CHAD	Consolidated Human Activity Database
CMB	Chemical Mass Balance
CO	Carbon Monoxide
CSN	Chemical Speciation Network
DPA	Daily Path Area
GPS	Global Positioning System
IRB	Institutional Review Board
KDE	Kernel Density Estimation
MADRES	Maternal And Developmental Risks from Environmental and Social Stressors
MCH	Minimum Convex Hull
NDVI	Normalized Difference Vegetation Index
NO_2	Nitrogen Dioxide
NOx	Nitrogen Oxides
O_3	Ozone
PEM	Personal Environmental Monitor
$PM_{2.5}$	Particulate Matter with aerodynamic diameter less than 2.5 μm

PM_{10}	Particulate Matter with aerodynamic diameter less than 10 µm
PMF	Positive Matrix Factorization (model)
RMSE	Root Mean Square Error
SD	Standard Deviation
SSI	Spatial Sciences Institute
STN	Speciated Trends Network
USC	University of Southern California
USEPA	U.S. Environmental Protection Agency
XRF	X-Ray Fluorescence

Abstract

Exposure to particulate matter air pollution with an aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), particularly during the 3rd trimester of pregnancy, has been associated with adverse impacts on maternal and fetal health. Pregnant women are mobile and locations they spend time in contribute to their personal $PM_{2.5}$ exposures, while their total exposures are the mixtures of multiple sources and affected by multiple factors. Environmental health disparities groups including racial and ethnic minorities, marginalized, and lower income populations are disproportionally burdened by elevated $PM_{2.5}$ exposure and may be more susceptible to its adverse health effects.

This dissertation used 48-hr integrated, personal $PM_{2.5}$ measurements and concurrent GPS records collected from 213 low-income, predominately Hispanic women in their 3rd trimester living in Los Angeles, CA, to investigate the impacts of activity spaces on personal $PM_{2.5}$ exposures (Chapter 2), derive the main sources contributing to personal $PM_{2.5}$ mass (Chapter 3), and determine the influence of microenvironmental exposures estimated with a stochastic exposure model and total personal exposures (Chapter 4).

This research found indoor sources dominated personal $PM_{2.5}$ exposures, where combined indoor source contributions (i.e., secondhand smoking, crustal) were more than triple those of outdoor sources (i.e., traffic, aged and fresh sea salt, and fuel oil). In addition, environmental exposures encountered within the activity spaces that participants frequented contributed significantly to personal $PM_{2.5}$ exposure, with greater exposure to parks and greenness linked with lower personal exposures. Finally, the simulated personal exposures better approximated the distribution of personal measurements with the addition of more refined indoor

source terms. However, total predicted $PM_{2.5}$ exposure was highly correlated with outdoor $PM_{2.5}$ which is contrary to the patterns observed with measurements.

Overall, the findings of this dissertation shed light on the complexity of sources and determinants of personal $PM_{2.5}$ exposures during pregnancy in an environmental health disparities population, as well as the need for refined exposure assessment methods to capture the true variability in exposure and aid in the design of relevant interventions to reduce exposures.

Chapter 1 Introduction

This chapter gives an overview of the dissertation research, starting by providing background to the research studies and knowledge gaps as well as introducing the research goals and study population. The dissertation structure is also laid out next for readers to follow.

1.1. Introduction

Air pollution is defined as particulate, gaseous, and (semi-)volatile matter "emitted from an anthropogenic, biogenic, or geogenic source" (Daly & Zannetti, 2007), present in the microscale, mesoscale, synoptic and global scale of atmospheric motions that can cause short- or long-term harm to human, animal or plant health, or to the environment (Hickey et al., 2014; Painter, 1974; Seinfeld & Pandis, 2006). In the twentieth century, several widely publicized incidents raised public concern about particulate matter (PM) air pollution effects on population health, such as the historical London Fog episode in 1952 with around 12,000 deaths (Bell & Davis, 2017). Since then, epidemiological studies have demonstrated that short- and long-term air pollution exposure is a significant risk factor for various diseases (Benbrahim-Tallaa et al., 2012; Brandt et al., 2014; Buffler et al., 2005; Chen et al., 2016; Gan et al., 2011; Kim et al., 2004) and increased mortality (Dockery et al., 1993) as illustrated by the Harvard Six Cities study (Dockery et al., 1993; Krewski et al., 2003).

Systemic inequities have resulted in persistent environmental health disparities, in which certain groups are heavily exposed to air pollution, leading to higher health risks (Bae et al., 2007; Houston et al., 2004; Tian et al., 2013). Studies have shown that low-income Hispanic populations, especially in California, are disproportionally burdened by elevated air pollution exposures and worse health outcomes, such as diabetes, lower bone mineral density, and respiratory diseases (Alderete et al., 2017; Chen et al., 2015; Chen et al., 2016; Houston et al., 2014; Pastor et al., 2004; Pulido et al., 1996). However, there is little known about the major determinants of $PM_{2.5}$ (particulate matter with aerodynamic diameter less than 2.5 μm) exposure in this population (i.e., where and when they experience the highest exposures, and which sources contribute the most to their personal exposures). Human mobility and the high spatiotemporal variability in some of the major sources contributing to $PM_{2.5}$ (such as traffic) provide an added complexity when trying to accurately estimate personal exposures in epidemiological studies.

For women during pregnancy, air pollution impacts on both their own as well as their fetus' health are major concerns (Dadvand et al. 2014; Ghosh et al. 2014). The health effects may vary in different time windows, since the fetus develops different organ systems at different weeks; therefore, exposure in different trimesters may have different health outcomes (Stieb et al. 2012; Zhu et al. 2015). Public health researchers have conducted studies focused on decreased birth weight related to in-utero exposure to $PM_{2.5}$ during pregnancy (Fleischer et al., 2014; Hyder et al., 2014; Pedersen et al., 2013; Rich et al., 2015; Stieb et al., 2012, 2016; Twum et al., 2016; Zhu et al., 2015). For example, several studies have demonstrated that $PM_{2.5}$ exposure during the 3rd trimester of pregnancy had the highest impact on the infant's gestational weight gain and birthweight (Huang et al., 2015; Rich et al., 2015; Romão et al., 2013; Savitz et al., 2014; Schembari et al., 2015).

Most of health studies focused on personal exposure to air pollution of outdoor origin with exposures assigned based on modeled pollutant distribution surfaces. The methods used to estimate these surfaces have evolved from the nearest monitoring site (i.e., EPA monitoring sites) (Ebisu et al., 2014; Harris et al., 2014), to spatially interpolated outdoor exposures based on multiple monitoring sites (Clark et al., 2010; Gauderman et al., 2005; Kim et al., 2004) and sophisticated spatiotemporal models of outdoor concentrations (Brunst et al., 2015; Chen et al., 2016; Gehring et al., 2010; Hyder et al., 2014). While spatiotemporal modeled air pollution surfaces provide the advantage of being able to assess the outdoor, residential exposures of large study populations, they suffer from exposure measurement error which usually leads to attenuated statistical power in epidemiological analyses.

Since individuals are mobile and spend the majority of their time indoors (Wallace, 1996), their "true" personal exposure is best approximated by the time-weighted average concentration they experience in and across several microenvironments, most commonly categorized as indoors, outdoors, and in transit (Gray et al., 2011; Zeger et al., 2000). The personal exposures for large populations can be estimated using microenvironment models (USEPA, 2020).

Personal monitoring is the gold standard approach to accurately capture the true personal exposures in the breathing zone. Accordingly, personal monitoring studies can disentangle the contributions of indoor and outdoor environments on personal exposures based on when and where those sampled have interacted with their environments (Adgate et al., 2004a; Rabinovitch et al., 2016; Steinle et al., 2015). These improvements have resulted in more accurate personal exposure estimates which greatly reduce measurement error and increase the understanding of how an individual's time-activity patterns affect personal exposures.

Furthermore, since $PM_{2.5}$ itself is a mixture of various organic and inorganic elements, its composition, and thus toxicity, may vary based on the sources from which it originated (Berger et al., 2018; Masiol et al., 2017; Zhai et al., 2017). Several studies have conducted source apportionment analyses on speciated $PM_{2.5}$ measurement data collected at designated U.S.

Environment Protection Agency (USEPA) ambient monitoring sites that are part of the Speciated Trends Network (STN). The aim of STN is to resolve the main sources that contribute to the outdoor $PM_{2.5}$ mixture and to investigate their impacts on the health of pregnant women (Bell et al., 2010; Dadvand et al., 2014; Ng et al., 2017; Pereira et al., 2014). However, identifying the main sources of personal $PM_{2.5}$ measurements will better serve health studies because toxicity may vary depending on this personal mixture. The information on major determinants (e.g., time-activities, spaces individuals frequented) and main sources of personal $PM_{2.5}$ exposures will facilitate the design of interventions that reduce exposures by connecting major sources and where and when pregnant women are exposed.

The paucity of knowledge of pregnant women's personal $PM_{2.5}$ exposures, especially the lack of information about the major determinants and main sources that contribute to personal $PM_{2.5}$ mass, hinders our ability to assess health effects and provide targeted interventions. This knowledge gap is often larger for populations burdened by environmental health disparities because very few studies have focused on their personal $PM_{2.5}$ exposures. This dissertation aims to produce a better understanding of personal $PM_{2.5}$ exposures for an environmental health disparities population, including the main determinants (e.g., activity spaces, time-activities) and sources that contribute to personal exposures during pregnancy. To accomplish this, this dissertation analyzed personal data collected from a sample of 213 women enrolled in the "Maternal And Developmental Risks from Environmental and Social Stressors (MADRES)" In-Utero Air Pollution Exposure Study. The sample participants are low-income, predominantly Hispanic pregnant women living in Los Angeles, CA, with personal $PM_{2.5}$ measurements and concurrent GPS tracking data collected over a 48-hr period in their 3^{rd} trimester. This study provided a unique opportunity to understand the personal $PM_{2.5}$ exposures of this at-risk population.

GPS records can be used to shape individuals' activity spaces and delineate their time-activities across microenvironments during the 48-hr sampling period; therefore, environmental exposures within activity spaces which might affect their personal $PM_{2.5}$ can be examined. Furthermore, the personal monitoring filters were speciated and analyzed for chemical composition information, which in turn was used to identify and resolve the major sources that contributed to these women's personal $PM_{2.5}$ exposures. The integration of individual-level GPS tracking and personal monitoring data further allowed us to explore how characteristics at the individual, residential neighborhood and activity space levels interact to affect total and source-resolved personal $PM_{2.5}$ exposures during pregnancy.

The MADRES participants in this study provide a convenient sample of women of childbearing age who are burdened by environmental health disparities in Los Angeles, CA for whom personal measurements were collected. A stochastic inhalation exposure model would be used to generate microenvironment level $PM_{2.5}$ exposures for this population without the personal measurements. The MADRES personal measurements were used to examine how well the model outputs approximated personal exposures. The results can help shape the model parameters and improve model personal exposures from multiple sources in large populations.

1.2. Dissertation Structure

The remainder of this dissertation is organized into three studies, each of which focuses on one aspect of understanding personal $PM_{2.5}$ exposures (Figure 1.1). Study 1 (Chapter 2) aims to investigate the main determinants that affected personal $PM_{2.5}$ exposures. The activity spaces were derived from GPS tracks to delineate the spaces in which individuals interact with their environments (Kwan, 1999; Newsome et al., 1998; Sherman et al., 2005). Generalized linear models were next applied to examine the impacts of the main factors, i.e., environmental exposures within activity spaces, time-activities, indoor environments, and outdoor $PM_{2.5}$, on variations of personal exposures.

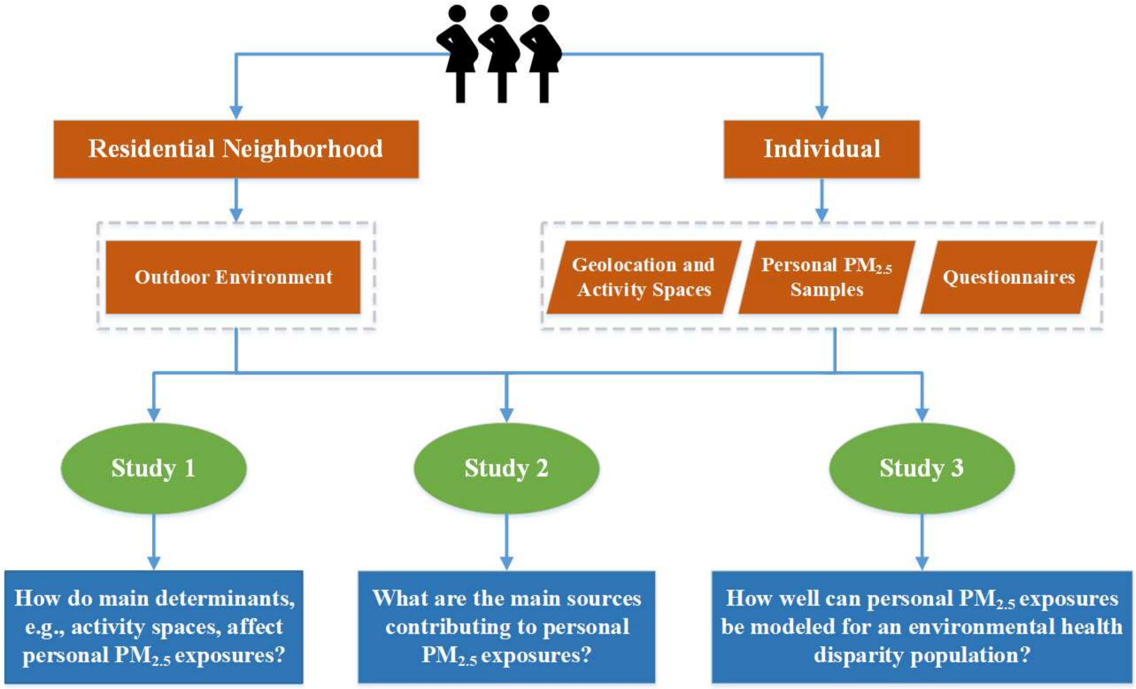

Figure 1.1. Dissertation research framework

Study 2 (Chapter 3) focuses on identifying the main sources that contributed to personal $PM_{2.5}$ exposures. The USEPA-developed Positive Matrix Factorization (PMF) model was used to resolve the main sources and quantify the mass contributions (Norris et al., 2014). In-depth personal data analysis was then conducted to confirm the source identities and their origins.

Study 3 (Chapter 4) examines how well personal $PM_{2.5}$ exposures can be modeled for environmental health disparities women with childbearing age. The USEPA-developed Air Pollutants EXposure (APEX) model was used to estimate personal exposures at the microenvironment level (USEPA, 2020). Multiple scenarios were set to compare the impacts of refining model parameters on personal estimates. MADRES personal measurements were then used to examine how well the model outputs approximated the actual (i.e., measured) exposures.

Ultimately, this research provided an opportunity to: (1) understand the personal $PM_{2.5}$ exposures of this environmental health disparities population during pregnancy, including major determinants, complex $PM_{2.5}$ sources, and the multiple microenvironments that contributed to personal exposures; and (2) lay out a foundation to reduce exposure measurement error in health studies, aid in designing relevant interventions to reduce health disparities. The results may inform appropriate interventions from urban planning perspectives, such as increasing greenness and park area city wide to reduce personal $PM_{2.5}$ exposures, which will potentially benefit both the mother's health and the child's health at birth and beyond.

The final chapter of the dissertation concludes the work by highlighting the major findings and implications of the three studies as a whole.

Chapter 2 The Impact of GPS-derived Activity Spaces on Personal $PM_{2.5}$ Exposures in the MADRES Cohort

This chapter is focused on investigating how exposures encountered within the activity spaces, as well as the time activities, home characteristics and residential neighborhood exposures, contributed to the personal $PM_{2.5}$ exposures during the 3rd trimester of pregnancy among MADRES participants. The chapter starts by introducing the research background, then followed by the data and methods used in this study, along with results, discussions and conclusion.

2.1. Introduction

Air pollution is a significant risk factor for various adverse health outcomes including respiratory infections (Kim et al. 2004), asthma (Brandt et al., 2014), cardiovascular disease (Gan et al. 2011), diabetes (Chen et al., 2016), and increased mortality (Bell and Davis 2017; Dockery et al. 1993; Garcia et al. 2016), among others. Studies of health impacts in pregnant women show air pollution exposure affects the mother's health (Dadvand et al. 2014; Ghosh et al. 2014) and may result in adverse birth outcomes (Fleischer et al. 2014; Pereira et al. 2014; Rich et al. 2015; Ritz et al. 2007). Third trimester exposure to $PM_{2.5}$ has been associated with low fetal birthweight (Hyder et al. 2014; Stieb et al. 2016; Twum et al., 2016; Zhu et al. 2015) and adverse health effects in childhood (Dadvand et al. 2011; Hsu et al. 2015; Rosa et al. 2020). Environmental health disparities also play a role, with specific racial or ethnic groups and lower socioeconomic status groups disproportionately exposed to higher concentrations of air pollution (Bae et al. 2007; Houston et al. 2004; Tian et al., 2013). In turn, these disparities are linked with increased susceptibility to multiple adverse health effects including obesity (Rossen, 2014), diabetes (Alderete et al. 2017; Chen et al. 2016), and respiratory outcomes (Grineski et al. 2015).

Most epidemiological studies rely on ambient concentrations to represent individuals' personal exposures to air pollution of outdoor origin (Gauderman et al. 2015; Pun et al. 2017). These coarse resolution approaches vary from assigning the value of the nearest monitoring site (Gauderman et al. 2015; Masiol et al. 2017) to spatially interpolated outdoor exposures based on multiple monitoring sites (Berger et al. 2018; Zhai et al. 2017) or sophisticated spatiotemporal models of outdoor concentrations (Beckx et al. 2009; Dadvand et al. 2013; Hu et al. 2015; McGuinn et al. 2016; Weaver et al. 2019). Several studies have used the aforementioned approaches to investigate the health effects of $PM_{2.5}$ exposure during pregnancy on maternal and child health outcomes, e.g. intrauterine inflammation (Nachman et al., 2016), stillbirth (Rammah et al., 2019), low birth weight (Hyder et al. 2014; Li et al., 2019; Twum et al., 2016), and childhood over-weight or obesity (Mao et al., 2017). While these models provide a cost-effective way to assess exposure to outdoor, residential air pollution in large population studies, they inherently suffer from exposure measurement error since they assume individuals are stationary, and they do not account for exposures encountered within activity spaces while mobile. They also ignore pollution sources in the indoor environment and time-activity patterns (i.e., time spent indoors or in transit).

Activity spaces represent “the local areas within which people move or travel in the course of their daily activities” (Gesler & Albert, 2000). Environmental exposures within these “local” areas or activity spaces are thought to be more correlated with personal exposures since they are more aligned with where and how individuals have contact or interact with their environments. As such, activity space methods provide promising advances in the field of environmental exposure science to understand health impacts (Golledge, 1997; Sharp et al., 2015; Sherman et al., 2005; Tamura et al., 2017; Wang et al., 2018). Several studies have used activity space methods to account for spatiotemporal variations in pollution in relation to an individual's whereabouts by recording when and where an individual move and how long they stay at one place or spend in transit (Gerharz et al., 2009; Goodchild, 2007; Nazelle et al. 2013; Nyhan et al. 2016; Steinle et al., 2015; Zenk et al. 2011). Several studies have correlated environmental features in the residential neighborhood (i.e., road network, green space) with personal exposures (Dadvand et al., 2012b; Kim et al., 2004). However, very few studies to date have investigated the role of activity space-based exposures on personal $PM_{2.5}$ exposures.

Moreover, personal monitoring can be used to measure air pollutant concentrations in the breathing zone and accurately assess total, personal $PM_{2.5}$ exposure (Dadvand et al. 2012b; Majd et al. 2018; Shang et al. 2019). Personal monitoring is considered the gold standard external exposure assessment approach since it captures personal, indoor, and outdoor sources of air pollution encountered across activity spaces and within microenvironments based on actual time-activity patterns. As such, it greatly reduces exposure measurement error and can increase statistical power to observe health associations when they exist (Gray et al., 2011; Zeger et al. 2000). However, despite its advantages, personal monitoring studies have been limited since they are generally more burdensome and expensive to conduct.

Among the few studies which measured personal $PM_{2.5}$ exposure in pregnancy, Dadvand et al. (2012b) monitored 54 participants for 48 hours and found higher residential neighborhood greenness was associated with lower personal, home-indoor, and home-outdoor $PM_{2.5}$ levels. Greenness was also associated with more time spent at home, outdoors. In a study of 17 pregnant women in the 3rd trimester, Zamora et al. (2018) found that personal $PM_{2.5}$ exposure was frequently more than double ambient concentrations, and the majority of $PM_{2.5}$ mass came from the indoor residential environment. Jedrychowski et al. (2006) found a significant positive association between personal $PM_{2.5}$ exposures and residential proximity to industrial plants in 407 non-smoking pregnant women in the 2nd trimester. Taken together, these studies show that pregnant women's personal exposure to $PM_{2.5}$ can be impacted by a variety of factors including indoor sources, time-activity patterns, and exposures encountered within residential neighborhoods and activity spaces.

Therefore, this research project aimed to investigate how exposures encountered within activity spaces contribute to $PM_{2.5}$ exposures during the 3rd trimester of pregnancy, using highly resolved personal exposure and geolocation monitoring data. The relationships between personal $PM_{2.5}$ measurements and GPS-extracted activity space-based exposures and time-activity patterns were first examined; then a model was built to explain the variability in personal $PM_{2.5}$ exposure based on these as well as individual and residential neighborhood characteristics to identify key exposure determinants in an environmental health disparities population of primarily low-income, Hispanic pregnant women living in Los Angeles, CA.

2.2. Method

Personal and environmental data used in this research, along with the main analytical methods, are laid out in this section.

2.2.1. Data Collection

Given the MADRES personal data used in this study, firstly the study design for MADRES cohort is briefly introduced here, followed by the description of the personal data used in this study including 48-hr personal $PM_{2.5}$ measurements, the concurrent GPS tracks, and questionnaire answers.

2.2.1.1. Study design

This study recruited 213 women who were enrolled in the MADRES cohort study during their 3rd trimester visit for this intensive 48-hour personal $PM_{2.5}$ exposure monitoring study between October 2016 and March 2020 (Appendix A, Table S2.1). MADRES is an ongoing prospective pregnancy cohort with the goal of understanding environmental and social determinants of maternal and child health outcomes among predominantly low-income, Hispanic women and their babies. The details of eligibility, enrollment, and follow-up in MADRES are described elsewhere (Bastain et al., 2019). Here, the aspects related to this personal monitoring arm of the larger study are briefly outlined. MADRES women were eligible to participate if they were in the 3rd trimester at the time of recruitment, ≥18 yrs old, and could speak either English or Spanish fluently. Exclusion criteria included: (1) HIV positive status; (2) physical, mental, or cognitive disabilities that prevent participation; (3) current incarceration; or (4) living in a smoking household, defined as having at least one smoker living full-time in the same residence as the pregnant woman. In practice, the non-smoking household criterion was not applied consistently throughout the study and thus was eliminated. Informed consent was obtained for each participant. The University of Southern California's Institutional Review Board (IRB) approved the study protocol.

2.2.1.2. Personal $PM_{2.5}$ exposure and geolocation monitoring

Once consented, participants were asked to wear a customized crossbody purse that contained all the sampling devices for 48 hours as they conducted their usual daily activities. The purse contained a personal Gilian Plus Datalogging pump (Sensidyne, Inc.) that was programmed to sample air continuously through an inlet tube at a 1.8 LPM flow rate and a 50% cycle (starting midnight on day following recruitment till midnight of the second day of sampling, once 48 hours were completed). The tube was connected to a $PM_{2.5}$ Harvard Personal Environmental Monitor (PEM) size-selective impactor with a pre-weighed 37 mm Teflon filter loaded inside (2 µm pore size; Pall, Inc.) to collect a 48-hour integrated (or averaged) sample. The PEM sampling inlet was mounted on the purse's shoulder strap to sample air at the participant's breathing level. Pumps were flow calibrated with the specific PEM sampler prior to each deployment using a TSI Inc. flow meter. Participants were instructed to carry the purse and sampling apparatus with them at all times, with a few exceptions to reduce burden and improve wear compliance. These included when it was unsafe to do so (e.g., driving), while showering or in high humidity, while sleeping, or while staying in one physical room for a prolonged period. In these cases, they were instructed to place the sampler near them, elevated above ground level, away from walls, and unobstructed by any objects.

In addition, an Android smartphone was included in the purse with the madresGPS geolocation app pre-installed and programmed to log location (GPS and metadata) and motion sensor data and network connectivity status continuously at 10-sec intervals for the 48-hour monitoring duration. The madresGPS app logs timestamp, latitude and longitude, location accuracy (m), and source of location (i.e., smartphone GPS sensor or network (WiFi or cellular)). The GPS source provided altitude (m), velocity (m/sec), number of satellites in view and in use when available. Smartphones were connected to a power bank to ensure enough power for a 48-hr runtime. All sampling devices were demonstrated to participants at recruitment and then securely sealed in a dedicated section of the purse to prevent loss or damage.

Once the 48-hour monitoring period was completed, the sampling pump shut down and GPS app stopped logging data automatically. Trained bilingual staff arranged a home pickup visit usually on the following day to retrieve the sampling devices and complete a short exit survey with participants (described below). PEMs were disassembled and pump and GPS app data were downloaded (and decrypted in the case of GPS) on the same day in the USC Exposure Analytics Laboratory. Filters were then analyzed gravimetrically to determine post-sampling $PM_{2.5}$ mass after a minimum of 24 hours equilibration period using a MT5 microbalance (Mettler Toledo, Columbus, OH, USA) in a dedicated chamber.

2.2.1.3. Questionnaires

At enrollment and during the 1st, 2nd and 3rd trimesters, MADRES participants responded to interviewer-administered questionnaires during in-person visits or phone interviews by trained bilingual staff. Questions included demographics (age, race, education, marital status, household income, country of origin), housing characteristics such as type of dwelling and building age, indoor sources such as presence and use of gas stoves, heating, and current tobacco smoke exposure (primary and secondhand). Participants' residential locations were determined based on reported address at the 3rd trimester timepoint and geocoded for residential neighborhood exposure assessment.

Once the participants completed the 48-hour monitoring period, trained staff conducted an exit survey during the equipment pick up visit asking about sampling device wear times, time-activity patterns (e.g., time spent indoors and outdoors, commuting), home operation (e.g., ventilation), and presence of any significant indoor sources of $PM_{2.5}$ such as cooking or smoking during either day of the 48-hr sampling period. Variables were summarized as the maximum or largest response across both days for all questions. Exposure to secondhand smoke was determined based on a response of “a little”, “most” or “all of the time” to the following question: “How much of the time were you close to cigarette, cigar, hookah or pipe smoke from people smoking nearby”. Spending time outdoor near traffic was determined based on a response of “sidewalk along the road” or “parking lot” to the following question: “Where were you when you were outdoors in general”.

2.2.2. Data Analysis

Data analysis is laid out in this sub-section, starting by creating residential neighborhood exposures, followed by activity space-based exposures, and GPS-derived time-activity patterns.

2.2.2.1. Residential neighborhood environmental exposures

Residential neighborhoods were defined as areas including the residential location and its surroundings in several ways since the exact spatial extent of influence in not well known in the literature. These included the residence as a point location, the residential census tract (RN_ct), and three circular buffers of 100m, 250m, and 500m around the residence (RN_100m, RN_250m, and RN_500m).

First, daily ambient and traffic-related air pollution and meteorology were estimated at the residential point location (Bastain et al., 2019). Local traffic-related nitrogen oxides (NOx) exposure was estimated using the CALINE4 line source dispersion model (Benson, 1992). Nitrogen dioxide (NO_2), $PM_{2.5}$ and PM_{10} (particulate matter with aerodynamic diameter less than 2.5 μm and 10 μm, respectively), and ozone (O_3) concentrations were estimated using inverse-distance squared spatial interpolation of regulatory monitoring data from the USEPA Air Quality System (AQS). Meteorology (temperature, precipitation, specific humidity, relative humidity, downward shortwave radiance, and wind speed) was assigned based on a 4 km x 4 km gridded reanalysis model from Abatzoglou (2013). To correspond to the two sampling days, 48-hr integrated averages were calculated from these daily measurements.

In addition, several built-environment characteristics were assessed within the census tract and circular buffer defined residential neighborhoods during the 48-hr monitoring period, including walkability index score, Normalized Difference Vegetation Index (NDVI, the most commonly-used metric to quantify greenness), access to parks and open spaces, traffic volume on primary roads, and road lengths (primary roads, secondary roads, and local neighborhood roads and city streets). These geospatial data sources used for Los Angeles County are shown in Table 2.1. Road network data were categorized as primary roads (S1100, Interstate highways, and all other highways with limited access), secondary roads (S1200, main arteries and highways with at-grade intersections), local neighborhood roads and city streets (S1400, paved non-arterial street, road, or byway, abbreviated as minor streets) (https://www2.census.gov/geo/pdfs/reference/mtfccs2018.pdf) (Figure S2.1 shows a map of these three road classes in Los Angeles, CA).

2.2.2.2. Activity space-based environmental exposures

Activity spaces were constructed using the GPS 10-sec resolution data to examine how participants' mobility within 48-hrs affected their personal $PM_{2.5}$ exposures (Browning and Soller 2014; Crawford et al. 2014; Perchoux et al. 2016; Sherman et al., 2005; Tamura et al., 2017). GPS tracks were first processed to remove outliers or erroneous records and retain those with highest positional accuracy, especially when latitude and longitude were available from both GPS and network sources. Distance-based outliers were defined based on a maximum reasonable distance (100 mile/hour) traveled per time elapsed (using a threshold of 45 m/sec multiplied by time elapsed) and were replaced by the median location (latitude and longitude) within a moving, centered time window corresponding to approximately one minute (seven intervals).

Similarly, since the exact spatial extent of influence on personal $PM_{2.5}$ exposures is not known, three measures of activity spaces were constructed to examine which might correlate the most as follows: 1) Minimum Convex Hull (MCH) or the smallest area covering all the GPS points, 2) Daily Path Area (DPA) which focuses on the area along individuals' routes by buffering all GPS points to 500 m, and 3) Kernel Density Estimation (KDE) which focuses on the intensity of GPS points in space. KDE therefore implicitly accounts for duration of time spent at a certain location, since GPS points will be denser or more intense where participants spent most time with this equally spaced 10-sec GPS data resolution (Jankowska et al., 2015; Kwan 1999; Newsome et al., 1998; Sherman et al. 2005; Zenk et al. 2011). KDE was applied with multiple bins (i.e., 10, 25, 50 m) and neighborhood sizes (i.e., 100, 250, 500 m) to examine the suitable parameters in terms of its Impact on personal $PM_{2.5}$ exposures (referred to as K10/100m; K10/250m; K25/250m; K25/500m; K50/500m). The top 20th percentile area of intensity in each KDE activity space was also used to calculate exposures as a test of whether this might be adequately correlated with personal exposure and computationally simpler compared to using the entire KDE surface (i.e., K10/100m_{20p}; K10/250m_{20p}; K25/250m_{20p}; K25/500m_{20p}; K50/500m_{20p}).

The same built-environment characteristics (Table 2.1) and ambient $PM_{2.5}$ and temperature were also assessed within the activity spaces. Forty-eight-hour average ambient $PM_{2.5}$ concentration and temperature were estimated for 2016-2020 using Empirical Bayesian Kriging spatial smoothing to complement the inverse distance squared method described earlier.

Figure 2.1 illustrates how different activity space and residential neighborhood methods are used to calculate exposure along a theoretical GPS trajectory. The blue boundary shows an example MCH activity space, and the dark green boundary shows the DPA activity space. The light to dark green (10m bin, 100m neighborhood), blue (25m bin, 250m neighborhood), and

Table 2.1. Summary of geospatial data sources for residential neighborhood and activity space-based exposure assessment.

Parameter	Web Data Source
Park and open space area in 2018	https://data.lacounty.gov/Sustainability/LA-County-Parks-and-Open-Space-2018/98vt-tkkj
Normalized Difference Vegetation Index (NDVI) with 0.6 m resolution in 2018	https://datagateway.nrcs.usda.gov/GDGHome_DirectDownLoad.aspx
TIGER road network in 2018	https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2018&layergroup=Roads
Primary road traffic volumes in 2017	https://data.ca.gov/dataset/annual-average-daily-traffic-volumes
Walkability index scores at the Census 2010 block group level for 2015	https://catalog.data.gov/dataset/walkability-index
Ambient daily $PM_{2.5}$ and temperature for 2016-2020 from USEPA monitoring sites	https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw

orange (50m bin, 500m neighborhood) weights correspond to lowest to highest intensity within multiple KDE areas based on locations an individual spent the most time in. The top 20th percentile area of each KDE activity space is illustrated as weight 5 in Figure 2.1. Dark gray circles (buffers) and polygon (census tract) show the four residential neighborhood definitions surrounding the residential point location. Residential neighborhood and activity space-based exposures were derived in ArcGIS Pro 2.5 (Esri, Redland, CA).

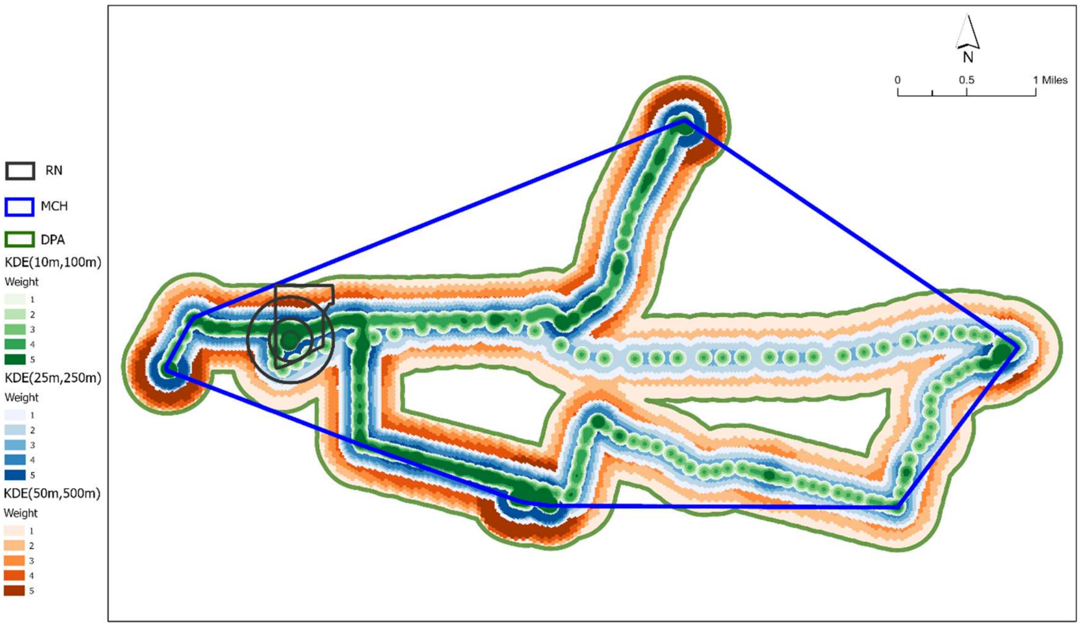

Figure 2.1. Illustration of multiple activity spaces and residential neighborhood

2.2.2.3. GPS-derived time-activity patterns

Time spent indoors or in-transit was derived from the processed GPS data using a previously published method that depends on time and distance thresholds (Cich et al. 2016; Li et al. 2008; Pérez-Torres et al., 2016; van Dijk 2018; Xiao et al. 2014). It identifies whether a participant was stationary or moving, as well as the duration of each activity or trip. The minimum time interval for a stay was defined as 30 mins. If the distance moved within 30 min was less than 500 m, the participant was identified as staying in one place. Once the stay points were identified, they were classified as home or non-home places by comparing them with the participants' known residential location with a 75 m buffer threshold to account for potential noise in geolocation. Twenty-eight participants did not stay overnight at their own residences during the 48-hr monitoring period, so the place where they stayed from midnight to early morning was determined to be their "home" place for the sake of deriving time-activity patterns. Time spent at home was assumed to be indoors and calculated in minutes and in percent (%) time. Categories of % time indoors were then created based on the data distribution (≤75%, 75 % to ≤90%, 90% to ≤95%, 95% to ≤98%, >98%) for use in the analysis.

2.2.3. Bivariate Analyses

Bivariate analysis were conducted to screen and select variables for the final regression model. The Kruskal-Wallis test was used to examine correlations of categorical variables with personal $PM_{2.5}$, including time-activity patterns, home characteristics, and indoor air pollution sources. Some variables were dichotomized or recoded to ensure more balanced and physically interpretable categories as follows: house vs. apartment, house built before vs. after 1980s, none or little of time vs. most or all of time for window open, none vs. a little, most, all of time of air conditioner used at home, less than vs. more than 75% of 48-hr period staying indoors, none or a little vs. most or all the time spent outdoors, less than vs. more than 30 mins gas stove use on daily basis, none vs. a little, most, all of time close to smoke from people smoking nearby, none vs. a little, most, all of time close to smoke from candles or incense burning nearby, and 0-30 mins vs. 30 mins to 1 hr vs. 1-2 hrs vs. more than 2 hrs in terms of commuting time. Sixteen variables with unbalanced values (≥85% of the records have one value) or too many missing values (>80%) were dropped from further analysis.

Spearman correlations were used to screen continuous variables such as residential neighborhood and activity space-based exposures for inclusion in the final $PM_{2.5}$ model and to evaluate them for collinearity with each other. Variables with absolute correlation > 0.05 or *p*-value < 0.25 in the bivariate analyses were retained for subsequent multivariate analysis. In addition, variables previously reported in the literature as important determinants of personal $PM_{2.5}$ exposure were also retained, including wind speed, relative humidity, year home was originally built, gas stove usage, secondhand smoking, and park area within activity space.

2.2.4. Multivariate Model

Generalized linear models were fit to explain the variability in personal $PM_{2.5}$ mass exposure in relation to multiple variables. These included time-activity patterns (*Time-Activity*), demographics (*Demographic*), home characteristics (*Home*), indoor sources ($Indoor_{sources}$), environmental exposures within residential neighborhoods ($EnvExp_{RN}$), and environmental exposures within activity spaces ($EnvExp_{ActSp}$). The model structure was as follows:

$$Y_{PM2.5} = \beta_0 + \beta_a * \sum_{a}^{T} Time - Activity + \beta_b * \sum_{b}^{D} Demographic + \beta_c * \sum_{c}^{H} Home + \beta_d * \sum_{d}^{I} Indoor_{sources} + \beta_e * \sum_{f}^{EA} EnvExp_{RN} + \beta_f * \sum_{g}^{ER} EnvExp_{ActSp} + \varepsilon \quad \text{Eq. (2.1)}$$

where β_0, β (a to f), and ε represent the intercept, coefficients, and error terms, respectively.

Variables selected in bivariate analyses were added to the model one at a time and retained if they were still significant at $p<0.1$ level. Variables that were highly correlated (or collinear) with each other, such as several measures of primary road length in activity spaces, were treated as alternative factors and substituted into the multivariate model to select the most significant. After the final list of variables was selected using this manual process, forward stepwise regression with the Sawa Bayesian Information Criterion (BIC) selection criteria was adopted for building the final model. Parameter estimates for all continuous variables were scaled to a one SD increase for comparison. BIC criteria was used since it penalizes the addition of more terms to the model to avoid overfitting. The adjusted R^2 and Root Mean Square Error (RMSE) were used to examine the fit of the model and *p*-value (Type III) was used to examine significance of included variables. All statistical analyses were conducted in SAS 9.4 (SAS Institute Inc., Raleigh, NC), and plots were generated using JMP Pro 16.1 (SAS Institute Inc., Raleigh, NC).

2.3. Results

2.3.1. Descriptive Statistics

Most of the participants (>98%) resided in central and east Los Angeles, CA. The majority were Hispanic (79%), employed during the 3rd trimester (41%), and with up to grade 12 education (54%). The mean age was 28 years at consent (range 18-45 years), and mean birth order of index child at the time of pregnancy (i.e., parity) was 2 (range 1-6). The majority of participants reported annual household incomes less than $30,000 (67%, N=135) (Table 2.2). In terms of personal monitoring device wearing compliance during 48-hr sampling period, 192 participants (91%) reported wearing it most of the time while awake, 183 (86%) reported putting it nearby as instructed while sleeping, and 200 (94%) reported putting it nearby as instructed when not wearing it during the day time (Table S2.2).

Table 2.3 presents distributions of home characteristics, indoor PM sources, and durations of selected activities for the participants. Based on the exit survey referring to the 48-hr sampling period, 60% of participants opened windows more than half of the time, 63% spent

Table 2.2. Descriptive statistics of participant demographics (N=213).

Variable	Mean (SD) or n (%)	Variable	Mean (SD) or n (%)
Maternal Age (years)	28.3 (6.0)	**Employment**	
Birth order of index child at time of pregnancy	2 (1.2)	Homemaker	58 (27.2%)
Race		Student	21 (9.9%)
White, non-Hispanic	12 (5.6%)	Employed	87 (40.8%)
Asian, non-Hispanic	2 (0.9%)	Temporary Medical Leave	9 (4.2%)
African American, non-Hispanic	24 (11.3%)	Unemployed	35 (16.4%)
Hispanic	169 (79.3%)	Missing	3 (1.4%)
Other	4 (1.9%)	**Household income in the last year**	
Missing	2 (0.9%)	Less than \$15,000	44 (20.7%)
Education		\$15,000 to \$29,999	47 (22.1%)
< 12th grade	51 (23.9%)	\$30,000 to \$49,999	29 (13.6%)
Completed high school	65 (30.5%)	\$50,000 to \$99,999	7 (3.3%)
Some college	63 (29.6%)	\$100,000 or more	8 (3.8%)
Completed college	25 (11.7%)	Don't know	76 (35.7%)
Some Graduate school	7 (3.3%)	Missing	2 (0.9%)
Missing	2 (0.9%)		

little or no time outdoors, 61% spent some time near traffic, and 34% spent more than 2 hrs commuting. In terms of indoor PM sources, 83 (39%) were exposed to smokers, and 52 (24%) were close to burning candles or incense. Based on the 3rd trimester questionnaire, 57% of participants lived in an apartment, 45% had a household size > 3 persons, and 43% lived in a home built after the 1980s. In addition, 139 (65%) used stoves > 30 mins/day at home during the 3rd trimester.

Summary statistics of 48-hr integrated personal $PM_{2.5}$ exposure and modeled outdoor $PM_{2.5}$ at residential location and within some activity spaces are shown in Table S2.3. Overall, 48-hr personal $PM_{2.5}$ exposures (mean = 23.3 μg/m^3, SD = 18.9) were much higher and more variable than corresponding outdoor residential levels (mean = 11.8 μg/m^3, SD = 5.5). Approximately 25% had personal exposures two to four times higher than outdoor residential $PM_{2.5}$. Outdoor $PM_{2.5}$ within multiple activity spaces was very similar to residential $PM_{2.5}$, which was also much lower compared to personal $PM_{2.5}$. Figure 2.2 shows the relationship between personal and outdoor $PM_{2.5}$ at residential location.

Table 2.3. Home characteristics, indoor sources, and durations of selected activities derived from questionnaires and exit survey (N=213).

Home Characteristics	n (%)	**Indoor Air Pollution Source**	n (%)
*Which best describes the home in which you currently live most of the time?		** How much of the time were you close to smoke from candles or incense burning nearby?	
House	75 (35.2%)	None of the time	160 (75.1%)
Apartment	122 (57.3%)	A little, most, or all of the time	52 (24.4%)
Missing	16 (7.5%)	Missing	1 (0.5%)
*How many people counting yourself live in your household?		*About how long is the gas stove, range or oven used on an average day while you are at home?	
1 and 2 people	26 (12.2%)	Less than 30 minutes	40 (18.8%)
3 people	30 (14.1%)	More than 30 minutes	139 (65.2%)
4 people	40 (18.8%)	Missing	34 (16.0%)
5 people	20 (9.4%)	**How much of the time were you close to cigarette, cigar, hookah or pipe smoke from people smoking nearby?	
More than 5 people	35 (16.4%)	None of the time	128 (60.1%)
Missing	62 (29.1%)	A little, most, or all of the time	83 (39.0%)
*About when was this home building originally built?		Missing	2 (0.9%)
Built after 1980s	91 (42.7%)	**Time-Activities**	
Built before 1980s	69 (32.4%)	**How much of the time did you spend outdoors (not commuting in a car, bus or train)?	
Missing	53 (24.9%)	None or a little of the time	135 (63.4%)
*Is there carpeting in your home?		Most or all of the time	77 (36.2%)
No	106 (49.8%)	Missing	1 (0.5%)
Yes	92 (43.2%)	**When outdoor, whether were you near traffic?	
Missing	15 (7.0%)	No	82 (38.5%)
Home Ventilation		Yes	130 (61.0%)
** How long the window open in your home?		Missing	1 (0.5%)
None or little of the time	85 (39.9%)	**How many hours did you spend on commute?	
Most or all of the time	127 (59.6%)	0 to 30 min	56 (26.3%)
Missing	1 (0.5%)	30 min to 1 hr	47 (22.1%)
**How much of the time was the air conditioner used in your home, when you were there with the sampler?		1 to 2 hrs	39 (18.3%)
None of the time	157 (73.7%)	> 2 hrs	41 (19.2%)
A little, most, or all of the time	55 (25.8%)	Missing	30 (14.1%)
Missing	1 (0.5%)		

* From the 3rd trimester questionnaire; ** Reported or derived from exit survey referring to 48-hour monitoring period.

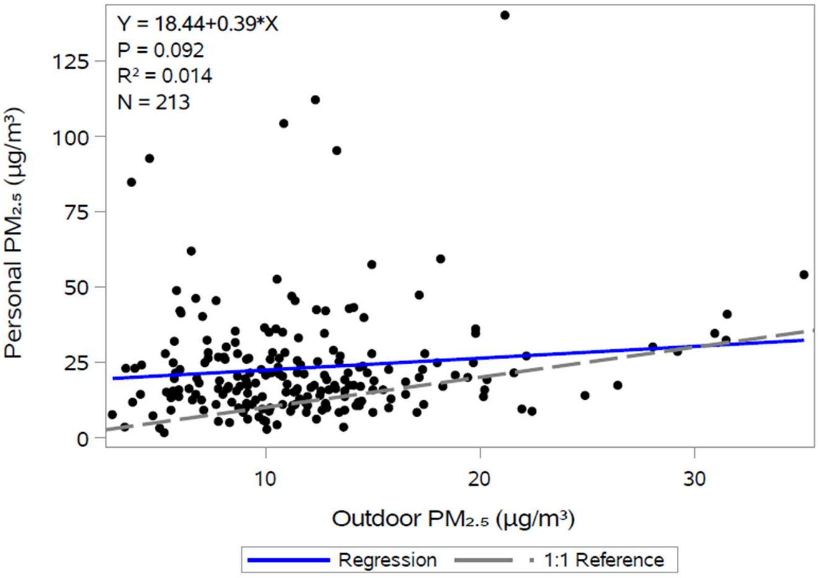

Figure 2.2. Regression plot between 48-hour integrated personal $PM_{2.5}$ exposures and outdoor $PM_{2.5}$ at the point of residence

2.3.2. Bivariate Analyses

Starting with questionnaire/exit variables, the bivariate results with personal $PM_{2.5}$ are shown in Table S2.4. The top five variables significantly associated with personal $PM_{2.5}$ exposure included the following (sorted by *p*-value): (a) home type; (b) home carpeting; (c) time spent close to smoke from candles or incense burning; (d) education level; and (e) number of people living in a household, parity and time spent outdoors. Living in an apartment (compared to a house), proximity to smoke from burning candles or incense, and spending more time outdoors was associated with higher personal exposures. Participants with 5+ people or more children in their household had higher personal exposures compared to less occupants or less children at home.

The descriptive statistics and correlation coefficient for environmental exposures within residential neighborhoods and activity spaces and time-activity patterns with personal $PM_{2.5}$ exposure are shown in Table 2.4. The top 3 variables positively associated with personal $PM_{2.5}$

Table 2.4: Bivariate results of personal $PM_{2.5}$ exposures with GPS-derived time activities and environmental variables.

Variables	N	Mean (SD)	Spearman Correlation (*p*-value)
Time-Activity			
***Time spent indoors	199	2,569.5 (523.4)	**-0.18** (0.009)
Residential Neighborhood Exposure			
Air pollutants			
$PM_{2.5}$ (µg/m^3)	209	11.8 (5.5)	0.09 (0.206)
O_3 (ppb)	209	24.8 (8.3)	**-0.14** (0.037)
NO_2 (ppb)	209	17.3 (8.6)	**0.15** (0.031)
Freeway and highway traffic-related NOx (ppb)	204	1.8 (1.8)	0.04 (0.530)
Meteorology			
Downward shortwave radiance (w/m^2)	209	224.6 (83.0)	**-0.17** (0.014)
Relative humidity (%)	209	60.2 (12.4)	-0.10 (0.167)
Wind speed (m/s)	209	2.4 (0.7)	-0.05 (0.439)
Greenness (NDVI) and Parks			
Mean NDVI within RN_100 m	213	-0.02 (0.04)	-0.05 (0.429)
Total park area within RN_250m	213	2957.6 (8166.1)	0.10 (0.147)
Road lengths and traffic volume			
Primary roads within RN_250 m	213	39.4 (115.1)	0.10 (0.140)
Secondary road within RN_ct	213	75.3 (281.9)	-0.06 (0.396)
Minor streets within RN_500 m	213	339.0 (102.7)	**-0.19** (0.006)
Mean traffic volume within RN_250 m	213	9535.2 (45898.4)	0.04 (0.589)
Built environment exposures			
Mean WIS within RN_250 m	213	14.4 (2.0)	-0.12 (0.087)
Activity Space Exposure			
Air pollutants			
Mean outdoor $PM_{2.5}$ within KDE area (K10/100m)	199	11.4 (5.5)	0.04 (0.530)
Meteorology			
Mean daily temperature within KDE area (K50/500m$_{20p}$)	199	18.3 (4.3)	**-0.15** (0.030)
Greenness (NDVI) and Parks			
Mean NDVI within KDE area (K25/250m)	199	-0.1 (0.1)	**-0.15** (0.037)
Mean park area within DPA	199	28,390.4 (59,052.1)	-0.06 (0.388)
Road lengths and traffic volume			
Primary road within KDE area (K50/500m)	199	425.7 (865.9)	0.12 (0.094)
Secondary road within DPA	199	453.6 (613.5)	0.04 (0.571)
Minor streets within KDE area (K10/100m)	199	126.7 (38.3)	0.10 (0.161)
Mean traffic volume within DPA	199	181,777.6 (108,620.1)	**0.14** (0.044)
Built environment exposures			
Mean WIS within KDE area (K10m/100n)	199	15.3 (2.1)	**-0.16** (0.027)

Nitrogen dioxide (NO_2), ozone (O_3), particulate matter with aerodynamic diameter less than 2.5 µm ($PM_{2.5}$), daily path area (DPA), kernel density estimation (KDE), residential neighborhood (RN).
*** From 48-hour GPS tracks. Values presented in bold font shows significant p-values at $p<0.05$ level.

(sorted by descending r value) were: (a) NO_2 at residential location, (b) mean traffic volume within DPA, and (c) primary road lengths within KDE area. The top 3 most negatively correlated variables with personal $PM_{2.5}$ were: (a) minor street lengths within RN_500m; (b) time spent indoors, and (c) downward shortwave radiance. $PM_{2.5}$ at residential neighborhood was more strongly associated with personal $PM_{2.5}$ compared to $PM_{2.5}$ within KDE area.

To illustrate how different residential neighborhood versus activity space methods could result in variable correlations with each other and with personal $PM_{2.5}$ exposure, primary roads were used as an example. Table S2.5 presents primary road lengths encountered by participants in their activity spaces or residential neighborhoods, along with the bivariate relationships with personal $PM_{2.5}$. Primary road lengths within KDE (K10/250m, K25/250m, K25/500m, K50/500m) activity spaces and within residential circular buffers (RN_250m, RN_500m) were most significantly associated with personal $PM_{2.5}$ (Spearman r 0.05 to 0.13). Table S2.6 shows the Spearman correlations between various activity space measures of primary road lengths ranging from low (blue) to high (red). The primary roads exposure variables which were most significantly associated with personal $PM_{2.5}$ were also highly correlated with each other ($r > .5$), so only one was selected to include in the final model (based on lowest p-value as explained earlier). Tables S2.7 and S2.8 (NDVI), and S2.9 (park area) show similar results for the remaining activity space and residential measures. The final list of variables selected for multivariate modeling is shown in Table 2.5.

Table 2.5. List of all potential variables considered for inclusion in the multivariate model.

Time-activity patterns	**Environmental exposures at residential neighborhoods**
**Time spent outdoors	O_3 (ppb)
**Time outdoor and near traffic	NO_2 (ppb)
***Time spent indoors	$PM_{2.5}$ ($\mu g/m^3$)
**Average commuting time	Relative humidity (%)
Demographics	Downward shortwave radiance (w/m^2)
*Education level	Wind speed (m/s)
*Birth order of index child at time of pregnancy	Mean length of minor streets within RN_500 m
Home characteristics	Average WIS within RN_250 m
*Home type	**Environmental exposures within activity spaces**
**Window open time	Average NDVI value within KDE area (K25/250m)
*Household crowding	Mean length of major road within DPA
*Home built year	Sum length of freeway within KDE area (K50/500m)
*Home carpeting	Mean traffic volume within DPA
**Air conditioner used at home	Mean park area within DPA
Indoor sources	Average daily $PM_{2.5}$ within KDE area (K10/100m)
**Time close to smoke from candles burning	Average daily temperature within KDE area ($K50/500m_{20p}$)
*Average stove use time at home	
**Having someone smoking nearby	

Nitrogen dioxide (NO_2), ozone (O_3), particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), daily path area (DPA), kernel density estimation (KDE), residential neighborhood (RN).
* From the 3rd trimester questionnaire; ** From exit survey referring to 48-hour monitoring period;
*** From 48-hour GPS tracks.

2.3.3. Multivariate Model

Table 2.6 summarizes the results of the final personal $PM_{2.5}$ model obtained with stepwise linear regression. Variables referring to parity, home ventilation, environmental exposures within selected activity spaces and residential neighborhoods, indoor sources, outdoor environment, and time-activities were included in the final model. Among them, longer window opening time, more greenness (higher NDVI) exposure within KDE area, longer duration of staying indoors, greater park area experienced within DPA, and higher exposure to minor streets within RN_500m were associated with lower personal $PM_{2.5}$ exposures. Whereas, parity, primary road exposure within the KDE area, outdoor $PM_{2.5}$ at residence, secondary road exposure within DPA, and candles or incense burning indoors increased personal $PM_{2.5}$ exposures. Commuting time was also included in the final model but seemed to have a non-linear relationship with personal $PM_{2.5}$. The final model (adjusted R^2 = 0.34 and intercept = 25.57) suggests that less than half of the variability in personal $PM_{2.5}$ mass was explained by all these factors. Figure 2.3 shows the plot of measured versus predicted personal $PM_{2.5}$ exposure based on the final model.

Table 2.6. Results of final generalized linear model of personal $PM_{2.5}$ mass exposure.

				Incremental model performance once variable added	
Variable	**Parameter Estimate***	**Pr > |t|**	**Pr > F**	**BIC**	**Adj. R^2**
Intercept	25.57		1.000	1120.07	0.00
Parity	5.81		<.0001	1101.19	0.10
Window open time (on average in 3rd trimester)			0.002	1092.79	0.14
Less than half of the time	ref				
Half to all the time	-5.48	0.027			
Length of primary road within KDE area (K50/500m)	2.82		0.005	1086.71	0.17
Average NDVI value within KDE area (K25/250m)	-3.09		0.018	1082.89	0.19
Average time of commute (in 48 hours)			0.013	1077.58	0.23
None	ref				
<= 1 hr	-0.65	0.893			
1-2 hrs	7.29	0.139			
2-3 hrs	-3.24	0.526			
More than 3 hrs	-7.62	0.154			
Missing	-1.36	0.803			
Duration of staying indoors (in 48 hours)			0.021	1074.14	0.27
≤75%	ref				
75% to ≤90%	-15.03	0.002			
90% to ≤95%	-20.09	<.0001			
95% to ≤98%	-9.99	0.029			
> 98%	-10.45	0.023			
Outdoor $PM_{2.5}$ concentration at residence	2.05		0.016	1070.72	0.29
Mean length of secondary road within DPA	5.57		0.043	1069.00	0.30
Mean park area within DPA	-3.62		0.023	1066.42	0.32
Candles or incense burning (in 48 hours)			0.047	1065.05	0.33
No	ref				
Yes	5.69	0.036			
Mean length of minor streets within RN_500m	-2.53		0.040	1063.55	0.34

Particulate matter with aerodynamic diameter less than 2.5 μm ($PM_{2.5}$), daily path area (DPA), kernel density estimation (KDE), residential neighborhood (RN).
*Parameter estimates of all continuous variables are scaled to one SD increase as summarized in Table S2.10.

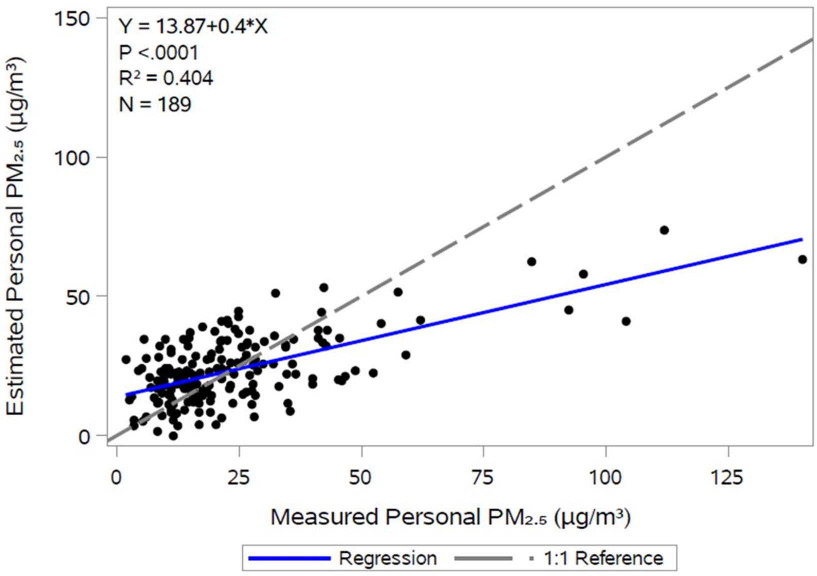

Figure 2.3. Measured versus predicted personal $PM_{2.5}$ concentrations and linear regression fit

2.4. Discussion

In this study, 48-hr integrated personal $PM_{2.5}$ measurements and concurrently recorded continuous GPS data were leveraged to assess environmental exposures in activity spaces, derive time-activity patterns, and investigate determinants of personal exposure among 213 pregnant women in the 3rd trimester in Los Angeles, CA. Given the higher burden of collecting personal monitoring data especially during pregnancy, this study provided a unique opportunity to understand the multiple complex factors that contribute to personal $PM_{2.5}$ exposure in this environmental health disparities population. The novel approach revealed that the exposures encountered within activity spaces, particularly greenness (NDVI), park area, and road lengths, were the significant contributors to $PM_{2.5}$ exposures. In addition, indoor environment, time-activities, and outdoor $PM_{2.5}$ at residential locations also affected the variation of exposures.

This study found that experiencing more park area and more greenness within individuals' activity spaces was associated with significant reductions in personal $PM_{2.5}$ exposure. To our knowledge, this is probably the first study to document this direct relationship between these natural and built environment features and personal $PM_{2.5}$ exposure during pregnancy. Most previous studies examining the impact of parks, green space or greenness on exposure and health used relatively coarse approaches or data (Chen et al., 2019; Crouse et al., 2019; Riggs et al., 2021; Son et al., 2021; Yitshak-Sade et al., 2019). For example, they used $PM_{2.5}$ values from monitoring sites or modeling estimates to approximate personal $PM_{2.5}$ exposures, calculated park area or average NDVI value within a fixed distance of residences, then established connections at the population level. Among the few personal monitoring studies, Dadvand et al. (2012b) examined the associations between personal $PM_{2.5}$ samples of pregnant women and surrounding greenness, represented by average NDVI within 100m/250m/500m residential buffers. They also found higher residential greenness was associated with lower personal $PM_{2.5}$ exposures, with strongest relationship seen for 100m buffer. In this study, NDVI exposure within multiple GPS-derived activity spaces were directly assessed that correspond to where participants actually went and spent time. The results revealed that KDE activity space greenness measures (with larger neighborhood sizes) were more strongly associated with lower personal $PM_{2.5}$ exposures compared to other activity spaces or residential neighborhood measures. This is probably because KDE measures are most representative of exposures experienced in space and time (of all the ones investigated). Others have also reported positive associations between greener residential neighborhood and birth weight (Dadvand et al., 2012a; Donovan et al., 2011). Taken together, the findings might suggest that increasing greenness in places where pregnant women visit and stay could result in beneficial reductions to personal exposure, which in turn might also improve physical health and well-being of both mother and her baby.

Furthermore, the results also revealed a significant effect of spending time near roads on personal $PM_{2.5}$ exposures, where primary and secondary roads within activity spaces were selected into the final model capturing potentially different aspects of road impacts on personal exposures. Primary road lengths within KDE (K50/500m) – which is a space- and time-integrated measure of being on or close to roads – was significantly associated with higher personal $PM_{2.5}$ exposure. In addition, mean length of secondary roads within DPA – a measure which strongly correlates with any encounter of secondary roads (which have a very specific geographic distribution in Los Angeles, CA, as shown in Figure S2.1) during participants' movement or mobility – was also significantly associated with higher personal $PM_{2.5}$ exposure. These results show how different activity space measures with potentially variable spatial extents could capture different aspects or contributions of the built environment to exposure.

This study found that the indoor environment has a large impact on personal exposure, and probably one of the largest in relative magnitude, both in terms of indoor sources such as combustion (e.g., candles or incense burning) and the number of children in the home (approximated by birth order or parity). These results are in line with other exposure studies showing indoor $PM_{2.5}$ had significant contribution to personal exposures (Brown et al., 2009; Kim et al., 2005; Koistinen et al., 2004; Lai et al., 2004; Zamora et al., 2018), or there was strong correlation between personal and indoor $PM_{2.5}$ (Adgate et al., 2002; Crist et al., 2008). The results showed that indoor combustion source contributed twice as much as outdoor $PM_{2.5}$ estimates to personal $PM_{2.5}$ (on a per SD change basis in outdoor $PM_{2.5}$). Given MADRES participants spent around 94% of their time indoors (Table S2.11), the indoor environment presumably dominated their personal exposures. Therefore, reducing indoor $PM_{2.5}$ sources could greatly reduce personal $PM_{2.5}$. Comparing to other studies which investigated indoor combustion sources mainly from smoking or cooking (Brown et al., 2009; Kim et al., 2005; Meng et al. 2009; Wheeler et al., 2011; Zamora et al., 2018), the results only identified candles or incense burning contribution to personal exposure. This could be because the survey measures did not fully capture the presence of secondhand smoking (no primary smoking in these participants) or cooking, or because the 48-hr sampling period did not always capture these if they occurred. Future planned chemical analysis of these personal sampler filters will help us resolve $PM_{2.5}$ sources and improve our understanding.

The results revealed that parity was more significantly associated with personal $PM_{2.5}$ than household size although these two variables are significantly correlated (Spearman r=0.24). The impact of multiple occupants in the home on personal exposure is less reported in the literature. These findings could reflect the fact that children (compared to adults) tend to be more active and stay in closer interaction with their mothers, or that mothers with more children cooked or cleaned more frequently for example. In addition, as reported in the literature an effect of window opening on reducing personal exposures was also found (Brown et al. 2009; Sarnat et al., 2006). Window opening increases ventilation in the home and could dilute PM concentrations emitted from indoor sources. It is also possible that window opening introduces PM of outdoor origin indoors when outdoor air quality is poor; however, the personal measurements were well spread over the sampling period which increases confidence in the representativeness of this finding across seasons (Table S2.1).

Individual's time-activities such as commuting and spending time near roads and traffic (regardless of activity) also affected personal $PM_{2.5}$ exposure. Previous studies also reported commuting impact on personal $PM_{2.5}$, with magnitude of influence highly dependent on commute modes and ventilation settings (Ham et al., 2017; Huang et al., 2012; Kaur et al., 2007;

Qiu and Cao, 2020). The non-linear or non-monotonous relationship between commuting time and personal $PM_{2.5}$ exposures in this study could be due to the fact of insufficient data on in-transit ventilation, commuting mode, or other factors known to modify exposure to $PM_{2.5}$ in transit. This study also found significant outdoor $PM_{2.5}$ contributions to personal exposure, and this is to be expected and highlights the rationale behind many studies of outdoor air pollution health effects that are using outdoor residential estimates as proxies of personal exposure to $PM_{2.5}$ of outdoor origin.

Finally, despite the sophisticated data collected in the research, the model did not explain a large portion of the variability in personal $PM_{2.5}$ exposure (Adj.$R^2 = 0.34$). This could be due to several reasons. One important reason could be that organic carbon (OC) contributes a large fraction of indoor and personal $PM_{2.5}$ mass, and there are major sources of OC indoors (Habre et al., 2014a, 2014b; Turpin et al., 2017). Turpin et al. (2007) found organic particulate matter was the major constituent of $PM_{2.5}$ generated indoors, which contributed 48% of $PM_{2.5}$ mass inside individual homes in Los Angeles. Habre et al. (2014a) attributed 46% of indoor $PM_{2.5}$ mass to indoor sources related to OC in New York. Other studies also confirmed large contributions of OC or organic matter to indoor or personal $PM_{2.5}$ (Hasheminassab et al., 2014; Habre et al., 2014b; Schachter et al., 2016; Shang et al., 2019). This study was not able to measure OC in this study using Teflon filters; therefore, a large portion of the PM mass could be missed this way (and especially OC1, the most volatile thermal fraction of OC). Other reasons could relate to the complexity of personal exposure and the multiple factors that contribute to it, where despite the sophisticated data collection and modeling, other important determinants of exposure might not have been captured. For example, there was not information on cleaning, vacuuming or dusting which resuspend particles and dust and could have contributed to personal exposures (Habre et al., 2014a; Hasheminassab et al., 2014; He et al., 2004; Koistinen et al., 2004; Long et al., 2000; Molnár et al., 2014). Some home characteristics, e.g., type of residence, carpeting or AC usage, were associated with personal $PM_{2.5}$ in bivariate models ($p < .15$) but ended up dropping out in multivariate model. Factors such as secondhand smoking and cooking in this study, which are well-recognized as important contributors to indoor and person exposures (He et al., 2004; Hu et al., 2012; Long et al., 2000), did not meet the bivariate screening criteria for multivariate analysis, and this could depend on the form of questions used or other biases. Data on these factors were collected in the questionnaires; nonetheless, if the question did not have enough resolution or the data did not have enough variability to capture the real complexity of these factors, the ability to model their full contribution to personal $PM_{2.5}$ might be limited.

The strengths of this research include a study population selected from a highly characterized prospective pregnancy cohort in a health disparities population, the 48-hr integrated personal $PM_{2.5}$ monitoring and concurrent GPS data, and the sophisticated activity space modeling to incorporate mobility and capture environmental impacts on personal exposures. This rich dataset provided the ability to examine complex factors to understand personal exposure. Some limitations include small sample size which is characteristic of personal exposure studies that are more burdensome to conduct, no organic carbon measurements, and perhaps reduced generalizability of the findings to other areas that do not resemble Los Angeles, CA. However, the results may generalize to other environmental health disparities contexts and studies. The 48-hour monitoring period in the 3rd trimester might also not be representative of the full pregnancy or entire 3rd trimester exposure; however, the samples were somewhat evenly spread out across seasons and years of the study.

2.5. Conclusion

The findings show that environmental exposures encountered within activity spaces, along with indoor environment, time-activities, and outdoor $PM_{2.5}$, significantly contribute to personal $PM_{2.5}$ exposure during pregnancy. Characterizing the impact of environmental exposures and sources encountered in activity spaces and across microenvironments can shed light on solutions and interventions to reduce personal exposures. Especially the finding of a direct association between greater greenness exposure in the activity space and lower personal exposure in the 3rd trimester of pregnancy need to be noted which could have direct relevance to built-environment design and planning to promote health and well-being.

Chapter 3 Sources of Personal $PM_{2.5}$ Exposure in the MADRES Pregnancy Cohort

In this chapter, the main sources are first identified and their mass contributions to personal $PM_{2.5}$ exposure of MADRES participants in their 3rd trimester of pregnancy are quantified. The factors such as time-activity patterns, environmental exposures encountered within activity spaces, home characteristics, and outdoor environment at the residence that were correlated with these sources were examined next to further confirm their identities and understand their origin (i.e., personal activity related, indoor origin, outdoor origin). The chapter starts by introducing the research background, followed by the data and method used in this study, along with results, discussion and conclusion.

3.1. Introduction

Epidemiological studies have shown that prenatal exposure to $PM_{2.5}$ is associated with adverse maternal and fetal health outcomes (Dadvand et al., 2013; Hu et al., 2015; Jedrychowski et al., 2012). Exposure in the 3rd trimester of pregnancy specifically has been associated with low birth weight and other impaired growth outcomes given this is the time when most fetal weight gain occurs (Guo et al., 2018; Percy et al., 2019; Sun et al., 2016). The toxicity of $PM_{2.5}$ and its subsequent impact on health is driven by its chemical composition and main sources contributing to it (Berger et al., 2018; Hasheminassab et al., 2014a; Masiol et al., 2017; Rohr & Wyzga, 2012; Saffari et al., 2013; Stanek et al., 2011; Stieb et al., 2012; Sun et al., 2016; Zhai et al., 2017; Zhang et al., 2008). Personal exposure to $PM_{2.5}$ is impacted by indoor, outdoor, and personal activity related sources in the various microenvironments individuals typically encounter. For example, behaviors, time-activity patterns, and household, neighborhood or activity space characteristics can impact the types and quantities of sources individuals are exposed to (Chen et al., 2020; Larson et al., 2004; Shang et al., 2019). As such, identifying and quantifying the main sources of personal $PM_{2.5}$ can shed light on particular mixtures that might pose a greater risk and would otherwise be missed by investigating exposure to total $PM_{2.5}$ mass concentration as a whole. This is particularly important in environmental health disparities contexts and for specific vulnerable populations such as pregnant women for whom meaningful recommendations to reduce exposures and health risks are needed (Brown et al., 2007; Han et al., 2017; Hasheminassab et al., 2014a).

Earlier studies have resolved and quantified main sources of PM exposure using source- and receptor-oriented modeling approaches. Source-oriented approaches start at the source and model the emissions, transport, dilution, and transformation of pollutants and estimate concentrations at receptor sites for one or more specific sources (Kim et al., 2005; Lippmann, 2009; Reff et al., 2009). Based on the fundamental mass balance principle (Watson et al., 2008), the receptor-oriented approach utilizes speciated measurements at receptor sites or points of interest to identify the major sources (or source groups) impacting that receptor and quantify their respective contributions to the observed concentrations (Hasheminassab et al., 2014a, 2014b; Hopke, 2003). Two of the most commonly used receptor-oriented models are the Chemical Mass Balance (CMB) model which assumes that the major sources impacting a receptor site are known along with their profiles or chemical signatures (Fujita et al., 2003; Harley et al., 1992; Hasheminassab et al., 2013; Schauer et al., 2002; Zhai et al., 2017) and the PMF model which solves for and does not explicitly assume known sources and profiles (Berger et al., 2018; Brown et al., 2007; Hadley, 2017; Han et al., 2017; Hasheminassab et al., 2014a, 2014b; Heo et al., 2009; Hopke, 2016; Masiol et al., 2017; Paatero & Tapper, 1994; Pekney et al., 2006; Rohr et al., 2014; Song et al., 2001; Wang & Hopke, 2013).

And while several studies have derived outdoor air pollution sources (Arhami et al., 2009; Cheung et al., 2011a, 2011b; Daher et al., 2013; Hasheminassab et al., 2013, 2014c; Heo et al., 2013; Schauer et al., 1996; Sowlat et al., 2016) and investigated their health impacts (Bell et al., 2010; Dadvand et al., 2014; Ng et al., 2017; Pereira et al., 2014; Rohr et al., 2014; Schachter et al., 2016), very few studies have been able to accomplish this for personal exposure. For example, Hasheminassab et al. (2013) and Hasheminassab et al. (2014a) resolved several sources of outdoor PM (particle size range 0.25-10 μm) including vehicular emissions, wood smoke, natural gas combustion, ship emissions, secondary aerosols, fresh and aged sea salt, and soil/road dust. Through conducting concurrent indoor and outdoor PM sampling at three retirement homes, Hasheminassab et al. (2014c) found that mobile sources were the major contributor to both indoor (39±21%) and outdoor (46±17%) $PM_{2.5}$ mass in Los Angeles, CA. However, sources that contribute to personal exposures can be more complex or difficult to discern since individuals get exposed to $PM_{2.5}$ in multiple microenvironments and locations, while being mobile or stationary, sometimes in close proximity to indoor or personal activity related sources and while being impacted by outdoor or infiltrated air pollution (Jenkins et al., 1992; MacIntosh et al., 2000; Ott et al., 2006; Wallace, 1996). A few studies have examined sources of indoor and outdoor PM air pollution in residential settings, for example, in homes of children with asthma (Habre et al., 2014a, 2014b). They found that risk of asthma symptoms in children varied by $PM_{2.5}$ source (Habre et al., 2014b).

However, even fewer studies conducted source apportionment analyses on personal monitoring samples, and most have ranged from 12 to 48 hours in duration (Brinkman et al., 2009; Chen et al., 2020; Kim et al., 2005; Koistinen et al., 2004; Larson et al., 2004; Molnár et al., 2014; Ryan et al., 2015; Shang et al., 2019). Personal monitoring is considered to be the gold standard external exposure assessment method to accurately understand what individuals are exposed to in their breathing zones (MacIntosh et al., 2000; Ott et al., 2006). Nevertheless, due to the high cost and burden of collecting high quality personal exposure data, very few studies have been able to conduct this type of monitoring especially in pregnant women (Choi et al., 2006, 2012; Jedrychowski et al., 2004, 2009; Rundle et al., 2012; Tonne et al., 2004), and even fewer conducted source apportionment analyses on personal $PM_{2.5}$ samples (Minguillón et al., 2012). Özkaynak et al. (1996) found that personal exposure to PM_{10} in 178 nonsmoking residents in Riverside, CA, was much higher than outdoor and indoor concentrations, and that these only explained 16% and 50% of the variation in personal exposures, respectively. In addition, they reported that cooking and smoking were important sources of personal exposure and that indoor and outdoor measurements alone were not sufficient to fully capture variation in personal exposure. Minguillón et al. (2012) found cosmetics and train/subway sources among others contributed to personal $PM_{2.5}$ exposures of 54 pregnant women with wide variation in contributions across participants. They report that questionnaire data helped identify the train/subway source, but limitations (e.g., recall error, accuracy of time and location of travel and activities) could introduce noise when resolving the sources.

To the best of our knowledge, no studies to date have investigated sources of personal $PM_{2.5}$ exposure in an environmental health disparities population during pregnancy. This study aimed to understand the main sources and determinants of exposure for this specific vulnerable population using data from a personal monitoring sub-study of the MADRES cohort in Los Angeles, CA. MADRES aims to address critical gaps in understanding the impacts of air pollution, environmental exposures, and social stressors on the maternal and child health in a low-income, predominantly Hispanic women in urban Los Angeles (Bastain et al., 2019). To accomplish this goal, the personal $PM_{2.5}$ samples were analyzed first for chemical composition. Source apportionment analysis was next conducted using the USEPA PMF model (Norris et al., 2014) and the relationships between predicted source contributions and a suite of questionnaire-collected and GPS-derived activity space and residential characteristics, personal behaviors, and time-activity patterns were investigated to confirm source identities and understand what contributes to their variation.

3.2. Method

In this section, the personal and environmental data used in this research are described along with the USEPA-developed PMF model and the statistical analysis used to achieve the research goals.

3.2.1. Data Collection

The study design for MADRES is briefly described first. Then the personal exposure data of MADRES participants including personal $PM_{2.5}$ measurements, concurrent GPS tracks, questionnaires, and environmental exposures at residential locations and within GPS-derived activity spaces, along with EPA speciated data, are described.

3.2.1.1. Study design

A total of 212 women in their 3rd trimester who were enrolled in the larger MADRES cohort study were recruited into this personal monitoring sub-study between October 2016 and March 2020. MADRES is an ongoing prospective pregnancy cohort focused on predominantly low-income, Hispanic women and their babies residing in Los Angeles, CA. The details of eligibility, enrollment, and follow-up of MADRES participants are described elsewhere (Bastain et al., 2019). Briefly, eligible participants for this study were in the 3rd trimester at the time of recruitment, ≥18 years of age, and could speak either English or Spanish fluently. In the initial design, people living in a smoking household were excluded to reduce the impact from smoking on personal $PM_{2.5}$ exposures. However, the non-smoking household criterion was not applied consistently throughout the study and was eliminated. Informed consent was obtained for each participant. The University of Southern California's Institutional Review Board (IRB) approved the study protocol.

3.2.1.2. Personal $PM_{2.5}$ measurements

Personal, 48-hr integrated $PM_{2.5}$ measurements were collected using a Gilian Plus Datalogging Pump (Sensidyne, Inc.) operating on a 50% cycle at 1.8 lpm flow rate and connected to a $PM_{2.5}$ Harvard PEM size-selective impactor with a 37 mm Teflon filter (2 µm pore size; Pall, Inc.). Participants were asked to wear the sampling device for the entire data collection period with a few exceptions. These included when it is unsafe to do so (e.g., driving), showering, or sleeping, in which case they were instructed to place the device near them in an unobstructed location.

Filters were analyzed gravimetrically to determine post-sampling $PM_{2.5}$ mass using a MT5 microbalance (Mettler Toledo, Columbus, OH, USA) in a dedicated chamber at the USC Exposure Analytics Laboratory. Filters were then sent to Research Triangle Institute International (RTI Inc., Research Triangle Park, NC) to determine elemental composition of 33 species using X-Ray Fluorescence (XRF). The chemical components included barium (Ba), calcium (Ca), chlorine (Cl), copper (Cu), iron (Fe), potassium (K), magnesium (Mg), manganese (Mn), sodium (Na), nickel (Ni), sulfur (S), silicon (Si), titanium (Ti), zinc (Zn), aluminum (Al), bromine (Br), cobalt (Co), phosphorus (P), lead (Pb), selenium (Se), strontium (Sr), vanadium (V), cesium (Cs), zirconium (Zr), chromium (Cr), rubidium (Rb), arsenic (As), indium (In), silver (Ag), antimony (Sb), tin (Sn), cerium (Ce), and cadmium (Cd). Filters were also analyzed for concentrations of black carbon (BC), brown carbon (BrC), and environmental tobacco smoke (ETS) using a four-wavelength optical reflectance method (Lawless et al., 2004; Yan et al., 2011).

3.2.1.3. Questionnaires

MADRES participants filled out interviewer-administered questionnaires in trimester-specific visits and an exit survey after completing the 48-hr monitoring period. Data that might directly or indirectly relate to $PM_{2.5}$ sources and personal exposures were collected, including demographics (e.g., age, race, education, employment, income), pre-pregnancy body mass index (BMI), housing characteristics (e.g., type of dwelling, building age), time-activity patterns (e.g., time spent indoors and outdoors, commuting), home ventilation (e.g., window open, air conditioner use), current tobacco smoke exposure (primary and secondhand), and presence of any significant indoor sources of $PM_{2.5}$ such as cooking or candle burning (Bastain et al., 2019). Participants' residential locations at the 3rd trimester study timepoint were geocoded for residential exposure assessment.

3.2.1.4. Residential Environmental Exposure Assessment

Daily ambient concentrations of NO_2, $PM_{2.5}$, PM_{10}, and O_3 obtained from the USEPA AQS were interpolated at the residence using inverse distance squared weighted interpolation (Bastain et al., 2019). Daily local traffic-related NOx concentrations at the residence were estimated using the CALINE4 line source dispersion model by roadway class (Benson, 1992). Daily meteorology (temperature, precipitation, specific humidity, relative humidity, downward shortwave radiance, wind direction and wind speed) was assigned at the residence based on a 4 km x 4 km gridded model developed by Abatzoglou (2013). Forty-eight-hour integrated averages were calculated from all daily measurements to correspond to the personal monitoring period. Specifically, wind direction was the average direction of degree in 48-hr period, where a direction of 0 degrees is due North on a compass and a wind coming from the south has a wind direction of 180 degrees. For analytical purposes, we categorized wind direction into four categories as follows: 0-90 degrees as wind blowing from NE, 91-180 degrees as SE, 181-270 degrees as SW, and 271-360 degrees as NW.

3.2.1.5. GPS-Derived Time-Activity Patterns and Environmental Exposures within Activity Spaces

Participants' 48-hr GPS records were collected using smartphones with the madresGPS app pre-installed and programmed to log geolocation (GPS and metadata) and motion sensor data continuously at 10-sec intervals. Time-activity patterns were derived from analyzing GPS records. Using the method described in Cich et al. (2016), Li et al. (2008), Pérez-Torres et al. (2016), van Dijk (2018), and Xiao et al. (2014), durations of staying at home or other places were extracted, as well as time on the road. All stays were assumed indoors and time spent indoors in the 48-hr period were calculated in minutes then converted it to a percentage out of the total 48 hours for use in the analysis.

KDE activity spaces were also constructed for each participant based on GPS trajectories to examine how exposures encountered within correlated with sources, where KDE implicitly integrates time and space to account for durations of time spent at certain locations (Jankowska et al., 2015, 2017; Kwan, 1999; Newsome et al, 1998; Sherman et al., 2005; Zenk et al., 2011). KDE was applied with pre-defined bin (i.e., 25 m) and neighborhood sizes (i.e., 250 m) to examine the impact on personal $PM_{2.5}$ exposures (i.e., K25/500m).

Built-environment characteristics including NDVI (greenness), parks and open spaces, traffic volume on primary roads, walkability index scores, road lengths by categories (i.e., primary and secondary roads, and minor streets), ambient daily $PM_{2.5}$ and temperature were assigned for the KDE activity spaces (data sources described in more detail in Table 2.1). Geospatial analyses for creating activity spaces, residential neighborhoods, and environmental exposure data were conducted in ArcGIS Pro 2.5 (Esri, Redlands, CA).

3.2.1.6. EPA $PM_{2.5}$ Speciation Data for Los Angeles, CA

Ambient $PM_{2.5}$ speciated data was downloaded from the USEPA monitoring site located in downtown Los Angeles. The concentration of these $PM_{2.5}$ components are 24-hr averaged values, which are collected every three days from the Chemical Speciation Network (CSN) (Solomon et al., 2014). The data includes the measurement of the major chemical components of $PM_{2.5}$ using the Met One SASS/SuperSASS Teflon - Energy Dispersive XRF method, including carbonaceous material, and a series of trace elements.

3.2.2. Data Analysis

The analytical methods are laid out in this sub-section, starting with descriptive statistics and followed by performing of the PMF analysis to identify main sources, as well as bivariate analysis to further understand factors that influence the distribution of each source and help confirm its identity or origin.

3.2.2.1. Descriptive Statistics

The descriptive statistics were calculated in SAS 9.4 (SAS Institute Inc 2013) to check the distributions of population demographics, housing characteristics, home ventilation, indoor sources of $PM_{2.5}$, time-activities, personal $PM_{2.5}$ mass and the measured chemical components and optical carbon fractions.

3.2.2.2. Positive Matrix Factorization Analysis

The USEPA PMF 5.0 model was used to resolve and identify major sources of $PM_{2.5}$ and quantify their mass contributions using the measured chemical species concentrations and sample-specific uncertainties as inputs. Briefly, the PMF model uses factor analysis to identify source contributions and profiles for a given number of sources through solving the following equation (Norris et al., 2014; Paatero & Tapper, 1994; Paatero, 1997):

$$X_{ij} = \sum_{k=1}^{n} g_{ik} f_{kj} + e_{ij} \qquad \text{Eq. (3.1)}$$

where X_{ij} represents the concentration of chemical species j in sample i, g_{ik} represents the mass contribution of each factor k in sample i, f_{kj} represents the loading of chemical species j on factor k, and e_{ij} is the residual error for sample i and species j.

The PMF model solves Eq. (3.1) by minimizing the sum of squares object function Q for a given number of factors k (Brown et al., 2015; Paatero & Tapper, 1994; Paatero, 1997):

$$Q = \sum_{i=1}^{n} \sum_{j=1}^{m} [\frac{e_{ij}}{u_{ij}}]^2 \qquad \text{Eq. (3.2)}$$

where u_{ij} is the uncertainty of species j in sample i. The model decomposes the concentrations matrix into a contributions g matrix and profiles f matrix and constrains results to be positive (or not significantly negative) (Brown et al., 2007; Paatero & Tapper, 1994). Each observation is individually weighted by its uncertainty in Eq. (3.2); therefore, samples with higher analytical uncertainties will have less influence on the solution.

Based on the PMF-calculated signal-to-noise ratio (S/N), which indicates the degree of noise in each species' measurements (Norris et al., 2014), we categorized species with $S/N \leq 0.2$ as "Bad", species with $0.2 < S/N < 1$ as "Weak", and species with $S/N > 1$ as "Strong". "Bad" species were excluded from the subsequent analysis. "Weak" species were retained and used in the analysis; however, their uncertainty values were increased by a factor of 3 to reduce their impact on the solution. Although Pb and V had $S/N < 0.2$, they were included in the analysis as potentially important tracers of traffic and fuel oil, respectively, and set to “Weak”.

Of the 36 species measured, the following 16 were finally included in the PMF analysis as “Strong”: BC, BrC, Ba, Ca, Cl, Cu, Fe, K, Mg, Mn, Na, Ni, S, Si, Ti, and Zn. We also included 9 “Weak” species as follows: Al, Br, Co, ETS, P, Pb, Se, Sr, and V. $PM_{2.5}$ mass was designated as the total variable which automatically defaults to “Weak” to reduce its impact on the solution. An extra 10% modeling uncertainty was added in the model to account for sampling or modeling errors not captured in the sample-specific analytical uncertainties (Norris et al., 2014). In order to maintain sample size, missing values were replaced by the species’ median value. Out of all available samples, 2.3% (5 out of 217) were excluded as outliers from the analysis based on species’ concentrations.

The solutions with five to seven factors and 20 model runs were scanned first to decide upon a reasonable factor number. The Q values for no undue influence from outliers and no local minimum solution were checked next. Based on loading chemicals in profiles and prior knowledge, the optimal sources from PMF that provided the most physically interpretable solution were identified (Brown et al., 2007). Once the optimal factor number was decided, 100 model runs were executed and the convergent solution with the lowest Q_{robust} value, where Q_{robust} is the calculated goodness-of-fit parameter excluding points with uncertainty-scaled residuals greater than 4, was selected (Norris et al., 2014). Residuals were checked for normality, along with R^2 values in terms of whether species were well modeled.

Diagnostics analysis of Displacement (DISP), Bootstrap (BS) (100 bootstraps, 0.6 minimum correlation), and Bootstrap-Displacement (BS-DISP) were performed to estimate the variability in the PMF solution under different scenarios. DISP focuses on effects of rotational ambiguity in the profiles or loadings; BS identifies whether there are a small set of observations that can disproportionately influence the solution; and BS-DISP include effects of random errors and rotational ambiguity (Norris et al., 2014). Fpeak rotations, where positive *F* peak values sharpen the *F* matrix and negative values sharpen the *G* matrix were performed next. The optimal Fpeak value for solution rotation was chosen based on the smallest change in *Q* (or *dQ*) (Norris et al., 2014).

3.2.2.3. Bivariate analysis

To further confirm the identities and expected trends in the PMF-predicted source contributions, the relationships with several variables described earlier including demographics, time-activity patterns, home characteristics, indoor air pollutant sources, residential ambient air pollutant concentrations and meteorological conditions, and environmental exposures within activity spaces, were examined.

The descriptive statistics were calculated first and used to check the distribution of the final, PMF-predicted and rotated source contributions for normality and outliers. The Spearman correlations between the predicted source contributions (in mass concentration units) and between the sources and variables hypothesized to relate to personal $PM_{2.5}$ exposure from that source were calculated next. The Kruskal-Wallis test was then used to test whether source contributions were significantly different (rank test) across levels of categorical independent variables. Categorical variables with unbalanced values (≥85% of the records have one value) or with too many missing values (≥80% of the records have missing values) were excluded from the bivariate evaluation and dropped from further analysis.

3.3. Results

3.3.1. Descriptive Statistics

Most of the participants (>98%) resided in central and east Los Angeles, CA. The majority were Hispanic (78%), working (48%) during the 3rd trimester, and with up to grade 12 education (55%). The mean age was 28 yr at consent (range 18-45 yr), and mean parity was 2 (range 1-6). The majority of participants reported annual household incomes less than $30,000 (67%, N=135) and in terms of pre-pregnancy BMI, 63 participants (30%) were overweight and 82 (39%) were obese (Table 3.1).

Table 3.1. Descriptive statistics of participants demographics (N=212).

Variable	Mean (SD) or n (%)	Variable	Mean (SD) or n (%)
Maternal Age (years)	28.3 (6.0)	**Maternal Ethnicity and Origin**	
Parity	2（1.2）	Non-Hispanic	41 (19.3%)
Race		US-Born Hispanic	75 (35.4%)
White, non-Hispanic	12 (5.7%)	Foreign-Born Hispanic	87 (41.0%)
Asian, non-Hispanic	2 (0.9%)	Missing	9 (4.2%)
African American, non-Hispanic	23 (10.8%)	**Employment**	
Hispanic	166 (78.3%)	Homemaker	57 (26.9%)
Other	4 (1.9%)	Student	21 (9.9%)
Missing	5 (2.4%)	Employed	84 (39.6%)
Education		Temporary Medical Leave	9 (4.2%)
< 12th grade	50 (23.6%)	Unemployed	35 (16.5%)
Completed high school	66 (31.1%)	Missing	6 (2.8%)
Some college	59 (27.8%)	**Working Status**	
Completed college	25 (11.8%)	No	106 (50.0%)
Some graduate training after college	7 (3.3%)	Yes	101 (47.6%)
Missing	5 (2.4%)	Missing	5 (2.4%)
Pre-Pregnancy Obesity Categories based on Body Mass Index		**Household income in the last year**	
Underweight	6 (2.8%)	Less than $15,000	44 (20.7%)
Normal	57 (26.9%)	$15,000 to $29,999	47 (22.1%)
Overweight	63 (29.7%)	$30,000 to $49,999	29 (13.6%)
Class 1 Obese	51 (24.1%)	$50,000 to $99,999	7 (3.3%)
Class 2 Obese	18 (8.5%)	$100,000 or more	8 (3.8%)
Class 3 Obese	13 (6.1%)	Don't know	76 (35.7%)
Missing	4 (1.9%)	Missing	2 (0.9%)

Chemical component concentrations are provided in Table 3.2. The mean and SD personal $PM_{2.5}$ mass concentrations during the 48-hr sampling period were 22.3 and 16.6 µg/m^3, respectively. The optical carbon fractions BC, BrC, and ETS combined constituted on average 17% (3.7 µg/m^3) of the total $PM_{2.5}$ mass. Among the elemental components measured, S, Na, Si were presented at the highest concentrations.

Table 3.2. Chemical component concentrations (all in units of ng/m^3 unless otherwise noted).

	N	Mean	SD
$PM_{2.5}$ mass (µg/m^3)	209	22.33	16.61
Optical Carbon Fractions			
BC (µg/m^3)	209	1.05	1.71
BrC (µg/m^3)	206	1.08	0.82
ETS (µg/m^3)	210	1.58	6.11
Elements			
Al	212	1.76	6.68
Ba	212	2.01	1.92
Br	212	0.42	0.44
Ca	212	12.13	20.00
Cl	212	17.91	35.86
Co	212	0.07	0.11
Cu	212	2.65	1.73
Fe	212	17.31	15.69
K	212	14.96	20.11
Mg	212	5.53	8.86
Mn	212	0.36	0.41
Na	212	43.34	42.69
Ni	212	0.33	0.39
P	212	0.77	2.52
Pb	212	0.20	0.37
S	212	56.88	41.54
Se	212	0.22	0.26
Si	212	23.47	28.79
Sr	212	0.25	0.95
Ti	212	1.44	1.80
V	212	0.09	0.16
Zn	212	1.86	2.47

The distributions of home characteristics, indoor PM sources, and selected time-activities as reported in questionnaires or derived from GPS data are presented in Table S3.1 (Appendix

B). Based on the exit survey, 60% spent some time near traffic when outdoors, and 34% spent more than 2 hrs per day commuting during the monitoring period. When with the sampler, 60% of participants opened windows more than half of the time, 26% used air conditioning and 37% used fans at home. In terms of indoor PM sources, 80 (38%) were close to cooking smoke and 51 (24%) close to burning candles or incense, and 83 (39%) were exposed to smokers. Based on the 3rd trimester questionnaire, 56% of participants lived in an apartment, 44% were part of a household with > 3 persons, and 43% lived in a home built after the 1980s. In addition, participants' GPS-estimated duration of staying indoors at home was 78.5% (SD=19.6) and staying in non-home locations was 15.2% (15.7).

3.3.2. Positive Matrix Factorization Analysis

We replaced missing values of 14 observations with species' median values including $PM_{2.5}$ mass (3 observations), BC (3), BrC (6), and ETS (2). A five-factor solution combined the two sources later identified as fuel oil and secondhand smoking, while seven factors resulted in a non-interpretable factor with a single high loading of Zn, resulting in a six-factor solution as the optimal, physically interpretable solution (Q_{robust} =5845.3 and Q_{true}=6143.1). An Fpeak rotation of -0.1 was then applied with 100 bootstraps which resulted in no unmapped factors (compared to one factor with two unmapped bootstrap runs in the base model (Table S3.2)). These six factors together explained 48% of the variability in $PM_{2.5}$. The species BC, Cl, K, S, Ca, and Zn had non-normal residuals (Table S3.3). The PMF results are presented below for each predicted source along with any bivariate analyses that supported its identification or explained some of the variation in its mass contributions.

Traffic. The first source identified was traffic with high loadings of BC, Zn, and Ba (Figure 3.1). It contributed on average 2.4% of the personal $PM_{2.5}$ mass (Table 3.3). Traffic was

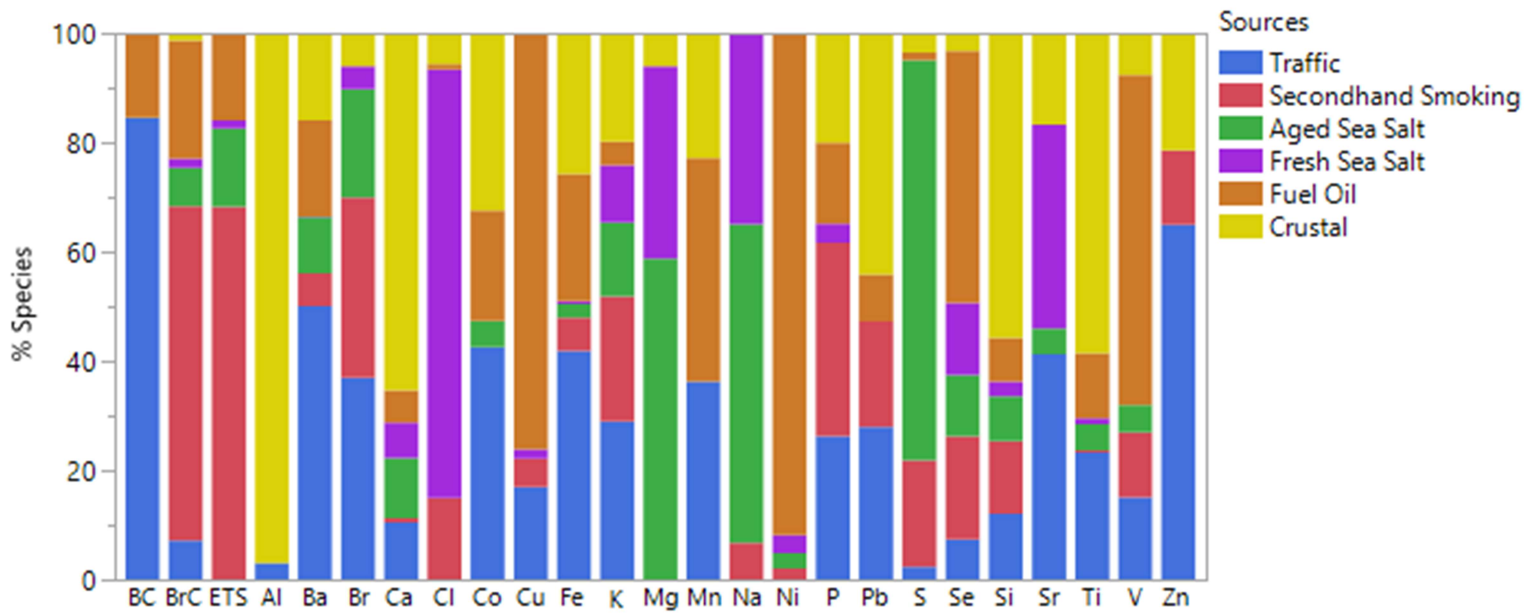

Figure 3.1. Source loading profiles (in % of species)

moderately positively correlated with crustal (described on page 58) and inversely correlated with fresh sea salt and fuel oil sources (Table 3.4). This source was positively correlated with outdoor NO_2 and $PM_{2.5}$ and negatively correlated with O_3 in the residential environment. It was also positively correlated with total traffic-related NO_x concentrations from local roadways around the residence, as modeled by the CALINE4 dispersion model. In addition, length of primary roads within KDE area was positively correlated with this source (Table 3.5).

Table 3.3. Source mass contributions.

Sources	Average mass contribution ($\mu g/m^3$) (SD)	Percent contribution to total $PM_{2.5}$ mass (%)
Traffic	0.4 (0.5)	2.4
Secondhand Smoking	11.7 (9.3)	64.2
Aged Sea Salt	0.9 (0.9)	4.8
Fresh Sea Salt	0.8 (2.0)	4.5
Fuel Oil	2.1 (1.6)	11.4
Crustal	2.3 (4.1)	12.6

Table 3.4. Spearman correlations among PMF-predicted source contributions, colored from low (blue) to high (red).

	Traffic	Secondhand Smoking	Aged Sea Salt	Fresh Sea Salt	Fuel Oil	Crustal
Traffic						
Secondhand Smoking	-0.09					
Aged Sea Salt	-0.01	**-0.29**				
Fresh Sea Salt	**-0.20**	**-0.24**	0.07			
Fuel Oil	**-0.20**	-0.03	-0.07	-0.01		
Crustal	**0.32**	-0.03	-0.08	-0.08	**0.14**	

Values in bold font represent significant p-values at p<0.05 level.

Secondhand Smoking. The second source we identified had a high loading of BrC and ETS (Figure 3.1). With an average mass contribution of 11.7 $\mu g/m^3$, it contributed the majority of personal $PM_{2.5}$ mass (64.2% on average) (Table 3.3). Participants living in apartments seemed to have slightly higher exposure to this source compared to those living in house (12.8 vs. 10.2

Table 3.5. Spearman correlations between PMF-predicted source contributions and variables related to personal activities, time-activity patterns, indoor and outdoor environment.

Source	Predictor	Correlation
Traffic	Outdoor (48-hour) air pollution at residence	
	O_3	**-0.35**
	NO_2	**0.61**
	$PM_{2.5}$	**0.43**
	Total NO_x from local traffic on Citilab road classes 1-5	**0.14**
	Length of primary roads within KDE activity space	**0.15**
Secondhand Smoking	Ambient air pollutant concentrations (overlapping 24 hours) at Downtown Los Angeles central site	
	Potassium Ion	0.12
	Potassium	-0.05
	Element Carbon	0.03
	Organic Carbon	0.09
Aged Sea Salt	Outdoor (48-hour) air pollution and meteorology at residence	
	O_3	**0.53**
	Wind speed	**-0.22**
	Temperature	**0.55**
Fresh Sea Salt	Outdoor (48-hour) meteorology at residence	
	Wind speed	**0.27**
	Relative humidity	**0.16**
	Ambient air pollutant concentrations (overlapping 24 hours) at Downtown Los Angeles central site	
	Ambient Chloride Ion	**0.25**
	Ambient Chlorine	**0.20**
Fuel Oil	Outdoor (48-hour) air pollution at residence	
	O_3	**-0.17**
	NO_2	**0.16**
Crustal	Outdoor (48-hour) air pollution and meteorology at residence	
	PM_{10}	**0.24**
	Relative humidity	**-0.47**
	Precipitation	**-0.16**

Values in bold font represent significant p-values at $p<0.05$ level.

μg/m^3, respectively, not significant, Figure 3.2). The secondhand smoking source was also negatively correlated with greater window opening time (11.7 vs.12.3 μg/m^3, not significant). Regarding the question of "if greater than none, how many people were smoking nearby" included in the exit survey, 70 participants (out of 212) provided positive answers and those experienced with more than one people smoking nearby had higher contributions from this source than those with only one person smoking nearby (13.1 vs. 10.9 μg/m^3, not significant). To eliminate the possibility that this could be an outdoor biomass burning signal, we checked its correlation with outdoor K, K+, elemental and organic carbon measures at the downtown speciation site (n=148), all of which showed insignificant weak correlations (Table 3.5).

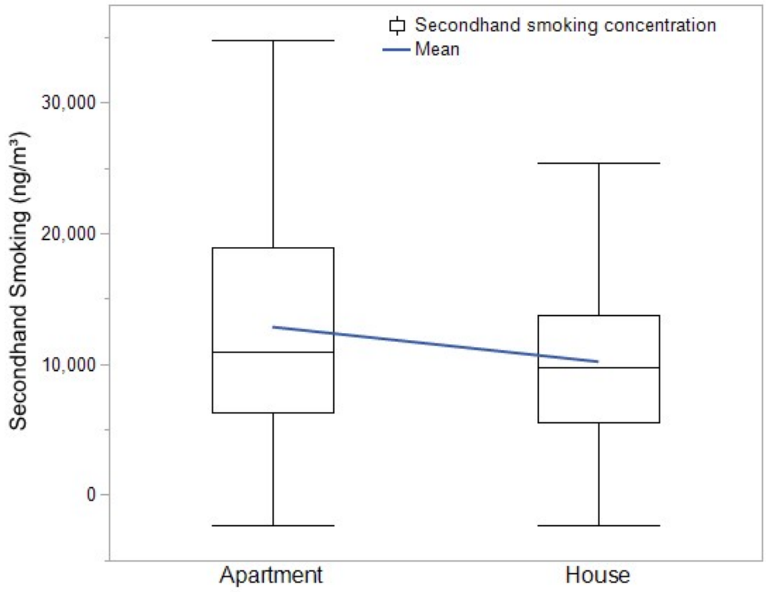

Figure 3.2. Relationship between secondhand smoking mass contributions and home type

Aged Sea Salt. The third source we identified had high loadings of Na, Mg, and S (Figure 3.1). It contributed on average 4.8% of the personal $PM_{2.5}$ mass (Table 3.3). Aged sea salt was negatively correlated with the secondhand smoking source (Table 3.4). It was strongly positively correlated with outdoor O_3 concentration and temperature and negatively correlated with wind speed (Table 3.5). Aged sea salt was also significantly positively correlated with window opening time, with an increasing trend in its average mass contributions from windows open none of the time (0.3 μg/m^3) to a little of the time (0.6 μg/m^3), most of the time (1 μg/m^3), and all of the time (1.2 μg/m^3) (Figure 3.3).

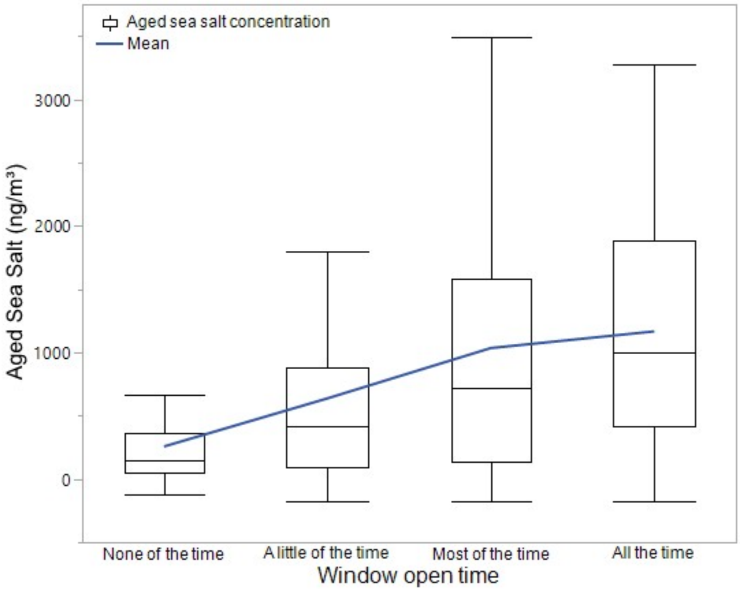

Figure 3.3. Relationship between aged sea salt and window opening time in the 48-hr monitoring period

Fresh Sea Salt. The fourth source we identified had high loadings of Cl, Na, and Mg (Figure 3.1). It contributed on average 4.5% of the personal $PM_{2.5}$ mass (Table 3.3). Fresh sea salt was negatively correlated with traffic and secondhand smoking sources (Table 3.4). The mass contributions of this source were highest on days when average wind direction originated from the west (NW followed by SW, significant, Figure 3.4). Fresh sea salt was also positively correlated with wind speed and relative humidity at residence. To eliminate the possibility of this being an indoor source correlated with aerosolized minerals from domestic water use or salt used in cooking (Özkaynak et al., 1996; Schachter et al., 2020; Wallace 1996), we checked its relationships with humidifier usage and time close to smoke from cooking, respectively. Even though the sample size was unbalanced (30 out of 212 reported using a humidifier), average mass contributions were lower (not significant) when people used a humidifier compared to not (0.9 vs. 0.5 μg/m^3, respectively). Similarly, mass contributions were lower when participants reported spending more time close to smoke from cooking in the 48 hours (and not significant).

In addition, fresh sea salt was moderately positively correlated with ambient Cl and Cl- as measured at the Downtown Los Angeles central site (Table 3.5).

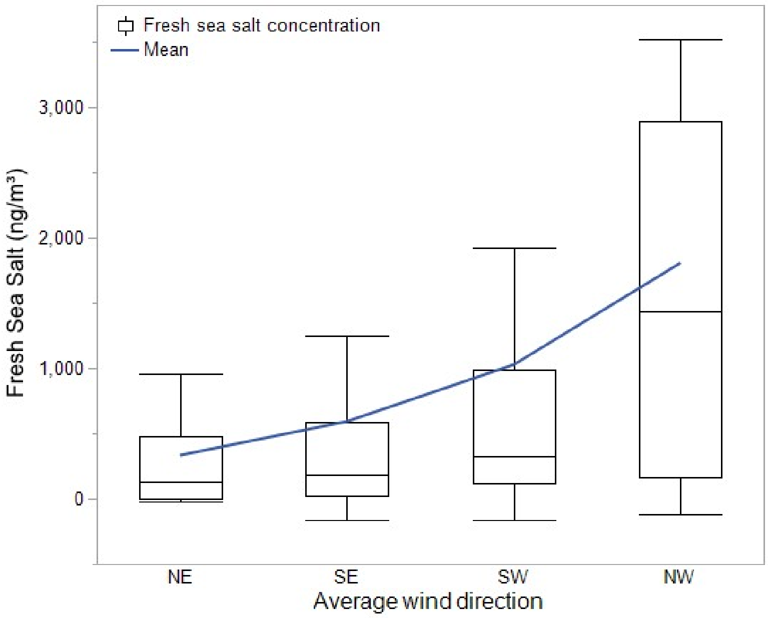

Figure 3.4. Relationship between fresh sea salt mass contributions and average wind direction in the 48-hr monitoring period

Fuel Oil. The fifth identified source had high loadings of Cu, Ni, and V (Figure 3.1). With an average mass contribution of 2.1 $\mu g/m^3$, it contributed 11.4% of personal $PM_{2.5}$ mass on average (Table 3.3). Fuel oil was positively correlated with crustal and negatively correlated with the traffic source (Table 3.4). The participants living in homes originally built before 1980 had higher exposures to this source than those living in newer homes (2.4 vs. 1.9 $\mu g/m^3$, not significant). In addition, it was positively correlated with outdoor NO_2 and negatively correlated with O_3 (Table 3.5).

Crustal. The last source we identified had high loadings of Ca, Si, Ti, and Al (Figure 3.1). It contributed the second largest share of personal $PM_{2.5}$ mass (12.6% on average), with an average mass contribution of 2.3 $\mu g/m^3$ (Table 3.3). Crustal was moderately positively correlated with traffic and fuel oil sources (Table 3.4). Households with more than three occupants were associated with greater contributions of this source than households with three or fewer occupants (1.3 vs. 2.8 $\mu g/m^3$, significant, Figure 3.5). It was also positively correlated with outdoor NO_2 and PM_{10} at the residence and negatively correlated with outdoor relative humidity and precipitation.

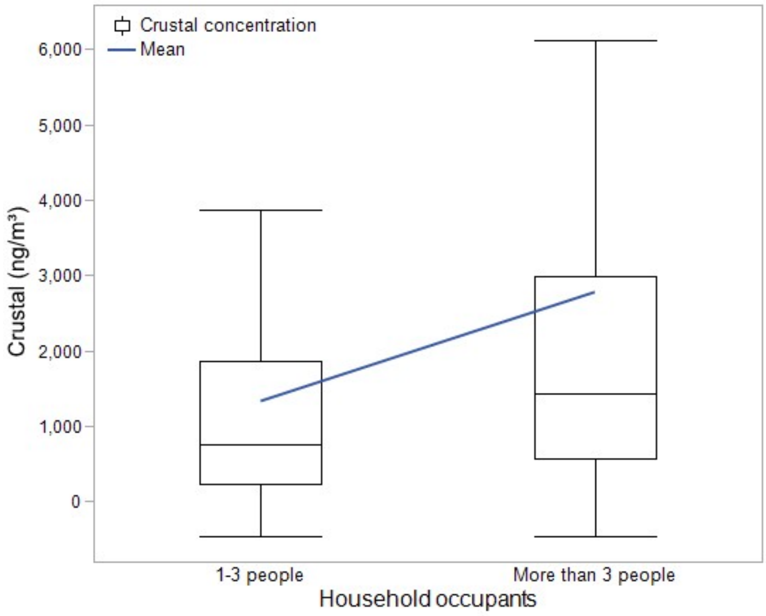

Figure 3.5. Relationship between crustal mass contributions and household occupants

3.4. Discussion

In this study, six main sources were identified along with their contributions to personal $PM_{2.5}$ mass concentrations collected from 212 low-income, predominantly Hispanic pregnant women living in Los Angeles, CA, during the third trimester of pregnancy. Of the six sources identified, secondhand smoking and crustal appeared to be of indoor origin, while traffic, aged and fresh sea salt, and fuel oil were of outdoor origin. Secondhand smoke was the single largest contributor to total personal $PM_{2.5}$ mass concentrations. The combined indoor source contributions (77%) were more than triple those of outdoor sources (23%), highlighting the importance of the indoor environment in contributing to personal exposures.

In order to avoid overloading the samplers with particles from primary tobacco smoke which would also overshadow any chemical fingerprints from other sources if present, by design, we excluded participants who reported smoking themselves (this did not occur in this population) or those with an active smoker permanently residing in their household (despite this latter criterion not being consistently applied throughout the study). Despite this, secondhand smoking was still identified as the source with the largest contribution to personal $PM_{2.5}$ exposures. The mass contributions of this source did not show any clear trends over time as the study progressed, suggesting that recruitment decisions did not significantly influence the findings. This source had high loadings of BrC and ETS, and some loadings of Br and K which were related to tobacco smoke in previous studies (Benner et al., 1989; Lawless et al., 2004; Müller et al., 2011). Secondhand smoke is a well-known contributor to indoor air pollution (Mueller et al., 2011; Nazaroff & Singer, 2004). The results showed that participants living in apartments tended to have marginally higher exposure to secondhand smoking than those living in detached houses. This could suggest greater potential of secondhand smoke infiltration from adjacent units in an apartment building or from visitors smoking (Fabian et al., 2016; Price et al., 2006; Wilson et al., 2011). Nevertheless, as both BrC and K are also strongly related to biomass burning (e.g., Hasheminassab et al., 2014a, 2014b; Meng et al., 2007; Palm et al., 2020; Runa et al., 2021), the correlations between secondhand smoking source and outdoor potassium were checked to eliminate the possible source of biomass burning.

The results showed both fresh sea salt and aged sea salt as outdoor sources, with high loading of Cl, Mg, Na, and Mg, Na, S, respectively. Previous work identified sea salt sources with similar loading profiles (e.g., Cheung et al., 2011a; Corral et al., 2020; Habre et al., 2021; Hasheminassab et al., 2014a, 2014b). Despite only having average wind direction over the 48-hr monitoring period (not most frequent wind direction), fresh sea salt mass contributions were higher with westerly winds and higher wind speeds, which provided greater potential for aerosolization and airborne transport of sea salt particles from the Pacific Ocean. Habre et al. (2021) found sea salt mass contributions to $PM_{2.5}$ mass in southern California to be highest in coastal communities. As fresh sea salt ages and undergoes photochemical reactions that also lead to secondary O_3 formation with warmer temperatures and more stagnant wind conditions (lower wind speed), chlorine is lost and sulfates are formed (Gard et al., 1998; Habre et al., 2021). Thus, aged sea salt resembles fresh sea salt in its loading profiles, except with S instead of Cl. Lower wind speed provides more chemical reaction time between the sea salt particles and contributes to the loss of chlorine and an increase in the formation of O_3 (Crawford et al., 2019; Knipping & Dabdub, 2003).

The high loadings of Al, Ca, Si is expected in natural crustal materials, and the lack of or less abundant loadings of Ba, Zn and Cu indicated that this was not resuspended road dust which could have tire and brake wear impacts (Cheung et al., 2011a; Lough et al., 2005). Crustal elements originate outdoors and can enter the indoor environment as windblown dust or as dust tracked indoors on residents' shoes. Once indoors, crustal materials will typically settle and get resuspended as indoor sources (or emissions of indoor origin) when disturbed by human movement or other activities (i.e. vacuuming). Therefore, the presence of more occupants in a household provides greater opportunities for re-suspension of crustal dust which mirrors the results reported here (Habre et al., 2014a). As such, crustal was labelled as an indoor origin source despite the possibility of our participants getting exposed to crustal dust outside of their homes as well.

The results indicate that fuel oil and traffic sources contributed to personal $PM_{2.5}$ exposures as well. Similar to previous studies, the fuel oil source had high loadings of Ni and V which are known tracers of heavy residual fuel oil combustion in large industrial applications and in marine engine emissions (Corbin et al., 2018; Corral et al., 2020; Larson et al., 2004; Maykut et al., 2003; Meng et al., 2007; Minguillón et al., 2012). BC serves as a marker for the traffic related source (Habre et al., 2014a; Hasheminassab et al., 2014b), while species such as Zn, Ba, and Fe come from motor vehicle exhaust emission, brake and diesel additives (Ålander et al., 2005; Corral et al., 2020; Meng et al., 2007; Onat et al., 2013). This source was correlated with residential estimates of CALINE NOx and outdoor pollutants related to traffic, which can be related to the finding that participants spent the majority of their time at home. The correlation between their traffic mass contributions and activity space based primary road exposures also revealed that these women visited many places, which were aligned with the time-activities derived from their GPS tracks.

The strengths of this study include the 48-hr personal $PM_{2.5}$ measurements and detailed chemical composition analysis that allowed us to apportion the major sources that contributed to personal exposures. By integrating concurrently collected questionnaire data and geospatially modeled environmental exposures in activity spaces (from GPS) and in the residential neighborhood, the results further corroborate these sources, their origin (primarily indoor vs outdoor), and exposure effects. With approximately three-fourths of personal exposures contributed by indoor sources, our findings highlight the importance of the indoor environment contributions to total $PM_{2.5}$ exposures during pregnancy and the potentially incomplete understanding of this population's exposures by solely relying on outdoor air pollution measures. The PMF model also only explained a portion of the variability in personal $PM_{2.5}$ mass concentrations (R^2 = 0.48). One possible reason could be that we did not measure organic carbon (OC) species in this study which are known to contribute a large fraction of indoor $PM_{2.5}$ mass concentrations (Habre et al., 2014a, 2014b; Turpin et al., 2017), and the possible volatilization of lightweight organic carbon fractions from the Teflon filters used in the sampling design. The sample size of the study, while considered large in personal monitoring settings, and the short monitoring period may limit the generalizability and representativeness of personal $PM_{2.5}$ exposures beyond this study area and across the full pregnancy and postpartum periods. However, this is one of the few studies to conduct a thorough characterization of sources impacting personal $PM_{2.5}$ exposures of predominantly Hispanic and low-income women during pregnancy in an environmental health disparities context.

3.5. Conclusion

$PM_{2.5}$ is a mixture of organic and inorganic elements, and its composition and thus toxicity can vary based on its sources. Given the complexity of $PM_{2.5}$ itself and multiple factors affecting personal exposures, it is critical to disentangle and understand the relative importance of different sources contributing to personal $PM_{2.5}$ exposures. Our findings also provide new insights of how multiple sources from indoor and outdoor environments contributed to the personal $PM_{2.5}$ exposures of low-income, predominantly Hispanic/Latina pregnant women in Los Angeles. The results may facilitate investigating the health effects related to each source, as well as recommending source-specific interventions to an environmental health disparities population during pregnancy.

Chapter 4 Modeling Personal $PM_{2.5}$ Exposures within Multiple Microenvironments

This chapter examined whether or not the APEX model developed by the USEPA could estimate the range of personal $PM_{2.5}$ exposures for MADRES participants, as well as how APEX parameters could be adjusted to capture more of the complexity in personal $PM_{2.5}$ exposures contributed by indoor sources and the interaction of the indoor and outdoor environments. The chapter starts by introducing the research background, followed by the data and methods used in this study, and then finishes up with results, discussion, and conclusions.

4.1. Introduction

Exposure to $PM_{2.5}$ is associated with several adverse health outcomes including respiratory and cardiovascular morbidity (Brandt et al., 2014; Gan et al., 2011; Kim et al., 2004). $PM_{2.5}$ exposure during pregnancy has also been shown to affect maternal (Dadvand et al., 2014; Ghosh et al., 2014) and fetal health (Dadvand et al., 2011; Fleischer et al., 2014; Hsu et al., 2015; Pereira et al., 2014; Rich et al., 2015; Ritz et al., 2007; Rosa et al., 2020). To accurately estimate its health risks, it is crucial to have accurate measures/estimates of total personal $PM_{2.5}$ exposure in health studies since this will reduce exposure measurement error and increase statistical power to observe associations (Baxter et al., 2013; Hu et al., 2017). In addition, given $PM_{2.5}$ itself is a mixture with several complex factors contributing to total personal exposure (i.e. time-activity patterns, indoor sources, behaviors, etc.), there is a need to understand where and when highest exposures occur, which sources contribute the most across various microenvironments people spend time in, and how to intervene to reduce risk. This is especially important for environmental health disparities research since disadvantaged populations often experience disproportionately higher exposures to certain sources and can be more susceptible to their adverse health effects (Bae et al., 2007; Houston et al., 2004; Tian et al., 2013).

Personal monitoring is considered the “gold standard” for assessing external exposure, in which participants carry or wear portable devices to sample air pollutants in their breathing zones as they go about their daily activities (Choi et al., 2006, 2008, 2012; Jedrychowski et al., 2004, 2009; Minguillón et al., 2012; Rundle et al., 2012). Nevertheless, due to the high cost and burden for participants and researchers, it is difficult to conduct high quality personal monitoring in large populations and over long periods of time. Therefore, models that can accurately predict total personal exposure for large populations and account for the various sources and factors that contribute to it would be highly desirable.

Since individuals are mobile, their personal $PM_{2.5}$ exposure is driven by their daily time-activities, by outdoor $PM_{2.5}$, and by $PM_{2.5}$ concentrations in microenvironments they spend time in (Duan 1982; Wallace, 1996; Wallace and Williams 2005). Accordingly, microenvironmental models have been developed to estimate personal exposure by integrating information on time spent within key microenvironments and $PM_{2.5}$ concentrations within them, assuming well-mixed conditions (Lai et al., 2004; Liu et al., 2003; Rabinovitch et al., 2016; Steinle et al., 2015). Several microenvironmental models have been developed to support population level applications (Berrocal et al., 2011; Breen et al., 2014; Hänninen et al., 2003; Hsu et al., 2020; Lim et al., 2012). Among them, the APEX inhalation exposure model developed by the USEPA has been widely used in air pollution exposure and risk assessment, as well as health studies (Dionisio et al., 2017; Johnson et al., 2018; Rosenbaum et al., 2008; Sarnat S. et al., 2013; USEPA, 2019a, 2020).

For example, Sarnat S.E. et al. (2013) found that APEX estimated personal exposures to carbon monoxide (CO) and NOx from outdoor origin produced better risk estimates of emergency department visits for asthma and wheeze than ambient concentrations in Atlanta, GA. However, Johnson et al. (2018) compared APEX-simulated microenvironmental $PM_{2.5}$ with corresponding measurements in three study areas within central Los Angeles, CA, and identified various sources of uncertainties in APEX inputs and predictions, namely lack of spatial resolution for ambient $PM_{2.5}$ and the non-representativeness of some of the APEX parameter (e.g., air exchange rate, decay rate) distributions.

APEX uses a stochastic, microenvironmental approach to estimate personal exposures to several air pollutants such as $PM_{2.5}$ for individuals randomly drawn based on age, race, and gender distributions within census tracts in specified geographic areas (USEPA, 2020). Activity patterns of simulated individuals are simulated by random draws from the USEPA's Consolidated Human Activity Database (CHAD) diaries, and their daily trajectories are assigned to user-selected microenvironments (McCurdy et al., 2000; USEPA, 2020).

Microenvironments and how they are operated can be customized for various settings or populations. For example, studies have shown that incorporating information on use of windows for ventilation and indoor source emissions may improve estimates of indoor concentrations (Johnson et al., 2018; Sarnat S.E. et al., 2013; Weisel et al., 2005). However, customization can also make it challenging to compare exposure estimates across models and studies. Previous studies have used fixed-site measured pollutant concentrations or exposures estimated from other methods to check the accuracy of APEX outputs (Johnson et al. 2018; Sarnat S.E. et al. 2013). Compared to the fixed-site monitoring data, Johnson et al. (2018) found APEX underestimated $PM_{2.5}$ concentrations in all of the microenvironments identified in this study.

In this study, personal $PM_{2.5}$ exposure measurements collected in the 3rd trimester of pregnancy in a sub-study of the MADRES pregnancy cohort were leveraged. MADRES aims to understand the effects of air pollution, environmental exposures, and social stressors on maternal and child health in a predominantly Hispanic, low-income population in Los Angeles, CA. Data from this personal monitoring sub-study provides a unique opportunity to compare to the distribution of APEX-predicted personal $PM_{2.5}$ exposures in a synthetic population simulated to resemble the larger environmental health disparities community the MADRES population (and eventually this sub-study) draws from. By learning from questionnaire information on key parameters (i.e., home ventilation, indoor sources, time-activity patterns, etc.) in MADRES, this study could also evaluate the extent to which the inputs need to be refined or resolved to get closer to reproducing the range of the personal measurement data for this particular environmental health disparities population.

Nevertheless, this comparison will not be perfect because: (a) APEX simulates hypothetical people and cannot be used to predict exposure for the same individuals and time periods in MADRES (USEPA, 2019a, 2019b, 2020); and (b) several assumptions are embedded in this comparison. For example, simulated individuals in APEX comprise a random sample drawn from the defined population universe in Los Angeles, while MADRES participants in the larger cohort from which the personal monitoring subset was selected were recruited from several prenatal care providers mainly serving medically underserved populations (Bastain et al., 2019). As such, the MADRES cohort was not designed to be a representative sample of environmental health disparities populations in Los Angeles, CA, but closely reflects a specific population's characteristics within the larger and more diverse Los Angeles, CA populations noted here. Therefore, for the purpose of this analysis, we assume that participants with personal monitoring data constitute an imperfect sample of MADRES, which is also a convenience sample of women of childbearing age living in Los Angeles neighborhoods experiencing environmental health disparities.

Therefore, the overall aim in this work was to examine whether APEX can estimate and explain personal $PM_{2.5}$ exposures seen in MADRES at scale, and if not, how much refinement or resolution of APEX inputs is needed to adequately reproduce the distribution and range of personal measurements. As such, the analysis spanned four stages: (1) running APEX with as close to default settings as possible to estimate personal $PM_{2.5}$ exposures for a simulated population with similar demographic characteristics as the MADRES participants; (2) incrementally adding and customizing parameters in APEX to capture more refined ventilation impacts and indoor source emissions in four scenarios; (3) comparing APEX estimates with personal measurements to select an optimal scenario; and (4) describing predicted exposures patterns and trends in the larger health disparities simulated population from the optimal, selected scenario.

4.2. Method

In this section, the personal exposure measurement data of the MADRES participants, the APEX model inputs, and the main methods applied in this research are described.

4.2.1. Data Collection

Given MADRES personal exposure measurement data being used in this study, the MADRES study and the sampling sub-study are introduced and the input data for APEX are described.

4.2.1.1. MADRES cohort and personal monitoring sub-study

MADRES is an ongoing prospective pregnancy cohort with the goal of understanding environmental and social stressors that might affect childhood and pregnancy-related obesity among predominantly low-income, Hispanic women and their babies in Los Angeles, CA (Bastain et al., 2019). Women at less than 30 weeks gestation, ≥18 years of age, and able to speak either English or Spanish fluently were recruited into MADRES from four prenatal care providers in Los Angeles (Bastain et al., 2019). Informed consent was obtained from each participant, and the USC's IRB approved the study protocol.

The personal monitoring sub-study recruited 213 women in their 3rd trimester of pregnancy from MADRES between October 2016 and March 2020. Their personal $PM_{2.5}$ exposures and geolocation were monitored using 48-hr integrated personal sampling and continuous GPS tracking at 10-sec intervals, respectively. In addition, an exit survey was conducted at the end of the 48-hr monitoring period to ask about home operation (e.g., ventilation) and presence of any significant indoor sources of $PM_{2.5}$ such as cooking or smoking during the 48-hr sampling period. Trimester specific questionnaires on demographics (e.g., age, race), indoor sources such as presence and use of gas stoves, home operation (e.g., windows open or not, AC usage), and current tobacco smoke exposure (primary and secondhand) were also used to define the study population, adjust the microenvironment settings, and add indoor emission sources to the APEX model, as described below.

4.2.1.2. APEX model input data

The APEX model provides flexibility in terms of setting microenvironment parameters and adding multiple emission sources to predict personal exposures to air pollutants for large populations. Therefore, five scenarios were set up by varying the parameters and emission sources, aiming to find the optimal settings for predicting personal $PM_{2.5}$ exposures for a large health disparities population. The model (Version 5.2, October 2019) was downloaded from the USEPA website (https://www.epa.gov/fera/human-exposure-modeling-air-pollutants-exposure-model). The 2010 census tract-based population counts (by gender, race and age), along with the activity diaries (questionnaires, events, and statistics) from the Consolidated Human Activities Database (CHAD) (McCurday et al. 2000) were downloaded from the same website. As the CHAD dataset covers the whole nation, the updated CHAD-California dataset was acquired from the USEPA support team.

In addition, the ambient regulatory $PM_{2.5}$ monitoring data (concentrations and district boundaries) for the modeling period of 2016-2020, as well as hourly temperature measurements and meteorology zones for the EPA monitoring sites located in our study domain were downloaded (https://aqs.epa.gov/aqsweb/airdata/download_files.html#Raw).

4.2.2. Data Analysis

This section describes the descriptive statistics gathered from MADRES personal measurements and by extracting time-activities from the GPS data, and then lays out the operational steps for the APEX model. Next, the model estimates and MADRES measurements are compared, and the APEX outputs are examined at the microenvironment level. The section closes with a description of the sensitivity analyses that were performed.

4.2.2.1. MADRES personal $PM_{2.5}$ exposure and geolocation monitoring data

Descriptive statistics were calculated on the personal $PM_{2.5}$ measurements to check their overall distributions. The personal measurements were also stratified by ethnicity to examine exposure variations between Hispanic and non-Hispanic women. Their 48-hr GPS tracks were used to extract the time spent indoors for comparison as well, using a previously published method (Cich et al., 2016; Li et al., 2008; Pérez-Torres et al., 2016; van Dijk, 2018; Xiao et al., 2014) with time (30 min) and distance (e.g., 500 m) thresholds to estimate the time spent indoors. The stay locations to the 3rd trimester residence were examined to confirm whether they stayed at home or not. There was not sufficient information to differentiate the microenvironments such as Outdoor, Near-Road and Vehicle and these were assigned to the "on-road" category.

4.2.2.2. APEX model runs

Microenvironment setting

The five microenvironments pre-defined by APEX were adopted, along with the methods (i.e., MASSBAL and FACTORS) for calculating $PM_{2.5}$ concentrations in each microenvironment (USEPA, 2019a, 2019b). The mass balance method (MASSBAL) was used to calculate concentrations for the Indoor-Residence and Indoor-Other microenvironments. MASSBAL assumes that an enclosed microenvironment (e.g., residence) is a single, well-mixed volume with the air concentration approximately spatially uniform, and the amount of outside air flowing into the microenvironment equals that flowing out of the microenvironment (USEPA, 2019b). Therefore, the $PM_{2.5}$ concentrations in microenvironments such as Indoor-Residence are affected by the inflow of air, outflow of air, removal of $PM_{2.5}$ due to deposition, filtration, and chemical degradation, and emissions from $PM_{2.5}$ sources inside Indoor-Residence. FACTORS was used to calculate $PM_{2.5}$ concentrations for the Outdoor, Near-Road and Vehicle microenvironments, in which it applies linear functions to relate microenvironment $PM_{2.5}$ concentrations to the current ambient concentration.

Defining the modeling domain

The framework for using APEX to estimate personal exposures is summarized in Figure 4.1. A circular study area with a 30 km radius that covered most of the MADRES participants' activity spaces was defined at the outset (Appendix C, Figure S4.1). The modeling period was set as October 1, 2016 to March 11, 2020, matching the data collection period of personal samples for the MADRES participants.

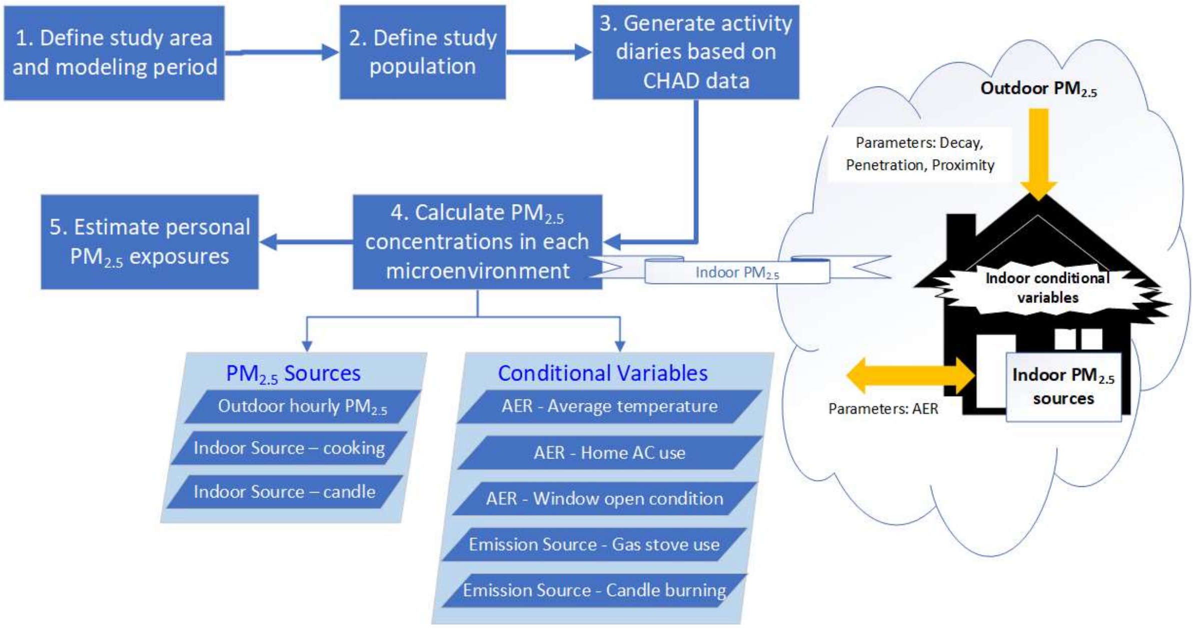

Figure 4.1. APEX model workflow

Defining the study population

The census tracts with centroids within the study area were used to establish the study domain for the simulated population. A total of 500 women aged 18 to 46 years living in Los Angeles County were randomly selected and each was assigned to a home sector and work sector, if employed. Their age and racial characteristics mirrored those in the 2010 census tract-level population count within the study area.

Generating activity diaries

APEX used the matching demographic characteristics (e.g., sex, race, employment status) for a simulated person and daily temperatures (e.g., MaxTemp, AvgTemp) for a simulated day to select an activity profile from the CHAD-California database. Then the model used the records matched on these characteristics to generate activity diaries and link them to microenvironments.

Calculating microenvironment $PM_{2.5}$ concentrations in five scenarios

APEX used the outdoor $PM_{2.5}$ concentrations to calculate hourly $PM_{2.5}$ concentrations in every microenvironment by linking the microenvironments people are in and the parameters such as air exchange rates (AER) and decay rate governing concentrations in those microenvironments. Given that multiple factors (e.g., keeping windows open or closed, emission sources) can affect microenvironment parameters such as AER (Abt et al., 2000; Cao & Frey, 2011; Habre et al., 2014a, 2014b; Howard-Reed et al., 2002; Jiao et al., 2012; Wallace et al., 2002; Yamamoto et al., 2010) and further affect microenvironment $PM_{2.5}$ concentrations, five scenarios were defined (labelled as *S1*, *S2*, etc., summarized in Table 4.1) for the model runs. The goal was to understand how the parameter setting changes for the Indoor-Residence microenvironment (e.g., probabilities of window opening depending on temperature, or emission rates of various indoor sources) might affect personal $PM_{2.5}$ estimates.

In *S1*, we used generic APEX-provided settings to calculate AER for Indoor-Residence (e.g., average temperature, the probability of using an air conditioner at home) and ambient $PM_{2.5}$ concentrations collected from EPA monitoring sites as the pollutant input. The parameters describing the distributions for microenvironmental concentrations estimates were taken from Johnson et al. (2018). Given the positive connections between windows open, air exchange rates

Table 4.1. Five APEX scenarios modeled in this simulation with associated conditional variables for the Indoor Residence microenvironment in each.

Scenarios	Conditional Variables	$PM_{2.5}$ Source Being Modeled
S1	Temperature ranges (categories) in Fahrenheit, Home AC probabilities (Yes/No)	Ambient
S2	Temperature ranges (categories) in Fahrenheit, Home AC probabilities (Yes/No), Home windows open (Yes/No)	Ambient
S3	Temperature ranges (categories) in Fahrenheit, Home AC probabilities (Yes/No), Home windows open (Yes/No), Home gas stove probability (Yes/No)	Ambient and indoor (gas stove use for cooking)
S4	Temperature ranges (categories) in Fahrenheit, Home AC probabilities (Yes/No), Home windows open (Yes/No), Home candle burning probability (Yes/No)	Ambient and indoor (candle burning)
S5	Temperature ranges (categories) in Fahrenheit, Home AC probabilities (Yes/No), Home windows open (Yes/No), Home gas stove probability (Yes/No), Home candle burning probability (Yes/No)	Ambient and indoor (gas stove use for cooking and candle burning)

and indoor pollutant concentrations shown in the literature (He et al., 2004; Howard-Reed et al., 2002; Sarnat J.A. et al., 2013; Schembari et al., 2013; Wallace et al., 2002; Yamamoto et al., 2010), window openings were added to the parameters specified in *S1* for calculating Indoor-Residence AER in *S2*. Based on previous studies, we assumed the window openings doubled AER (Howard-Reed et al., 2002; Wallace et al., 2002). Both *S1* and *S2* model the contribution of $PM_{2.5}$ of outdoor origin to total exposures. In *S3*, $PM_{2.5}$ emissions from gas stove use for cooking were added as an indoor source of $PM_{2.5}$, in addition to the parameters specified in *S2*. The probability of using gas stoves (Yes=0.92) was extracted from the MADRES questionnaire, and the use levels were taken from Hu et al. (2012). In *S4* indoor $PM_{2.5}$ emissions from candle or incense burning were added to the parameters specified in *S2*. The probability was again extracted from the MADRES exit survey (Yes=0.25), and the associated parameter distributions were also taken from Hu et al. (2012). Finally, in *S5* the concentrations from both indoor sources used in *S3* and *S4* were combined (cooking by gas stoves and candles/incense burning). The complete list of microenvironment parameters used for the five model runs along with their distributions is shown in Table S4.1 (Appendix C). To facilitate comparisons, we used the same seed number for all five scenarios.

Estimating personal $PM_{2.5}$ exposures

Based on the microenvironment concentrations, APEX then calculated the $PM_{2.5}$ exposure for each simulated person within every microenvironment. Time-averaged daily personal $PM_{2.5}$ exposures were also estimated for the simulated individuals.

4.2.2.3. Comparison of APEX estimates with MADRES measurements

The distribution of APEX predicted personal $PM_{2.5}$ exposures in *S1* were initially compared to the personal measurements using descriptive statistics, on a yearly basis and for the whole modeling period. Minimum and maximum values were used to check whether the range of APEX estimates were within personal measurements. Mean values were used to compare the overall performance for each scenario, while standard deviation values were used to check inter-personal variations in APEX predictions. The normality of personal $PM_{2.5}$ measurements and APEX estimates was checked and the Wilcoxon Sign Rank test was used to examine whether predicted vs. measured median $PM_{2.5}$ exposures were statistically significantly different. The same evaluations were conducted for *S2* through *S5* to check the impact of parameters (e.g., window conditions, indoor $PM_{2.5}$ sources) on estimated personal exposures and how well they reproduced the range of personal measurements.

The sum of minutes in each microenvironment were converted to the percentage duration from the overall modeling period or 48-hr sampling period for the aforementioned comparisons. We examined whether there were significant differences in terms of duration of time spent in In-

Residence and In-Other microenvironments as estimated by APEX or with GPS data from MADRES using Wilcoxon Sign Rank non-parametric tests. Given the personal exposures for MADRES participants were integrated values the estimated and measured $PM_{2.5}$ concentrations at the microenvironment level could not be compared. Therefore, the distributions of microenvironment exposures among APEX results estimated by the five scenarios were compared to highlight the impact of different parameters on microenvironment exposures. In addition, the hourly ambient $PM_{2.5}$ concentrations with predicted total personal and microenvironmental $PM_{2.5}$ exposures were compared.

Once the optimal scenario based on the closest reproducibility of the range of personal $PM_{2.5}$ measurements was selected, the predictions could be described in more detail. The durations (in percent) and exposures ($\mu g/m^3$) by microenvironment level are presented for the whole modeling period to gain a better understanding of time-activity patterns and associated exposures for APEX individuals. The microenvironment exposures were next compared on an hourly basis along with the personal exposures and ambient $PM_{2.5}$ and Spearman correlations among personal exposures, microenvironment exposures and ambient $PM_{2.5}$ were also conducted to check their relationships.

4.2.2.4. Sensitivity analyses

Since MADRES participants are low-income predominantly Hispanic pregnant women, and the APEX study area covers high income neighborhoods such as Beverly Hills, one of the concerns is that the simulated population might have very different socioeconomic characteristics and $PM_{2.5}$ exposures from the larger environmental health disparities population represented by MADRES participants. Therefore, sensitivity analyses were conducted to test whether including only MADRES census tracts in the simulation resulted in predicted exposures that more closely resembled the personal $PM_{2.5}$ measurements gathered in MADRES. To conduct this analysis, the overall modeling outputs into two groups – one group only including the estimated exposures for simulated individuals living in MADRES census tracts, and the other group only including the estimated exposures for those living in non-MADRES census tracts. The between-group differences was then calculated along with comparisons with personal measurements. Given MADRES participants are predominantly Hispanic women, tests were also conducted to see whether the limiting the simulation results to only Hispanic women resulted in more similar $PM_{2.5}$ estimates as well.

4.3. Results

Table 4.2 summarizes the demographic characteristics of the 500 individuals simulated with APEX and the MADRES participants. Since we used the same seed to initialize the model but different parameters and added indoor $PM_{2.5}$ sources in several scenarios, we observed slight differences in terms of population composition. MADRES participants were four years younger on average; and 79% of them were Hispanic, compared to just 52% in the model simulations.

Table 4.2. Demographic characteristics of simulated APEX and actual MADRES participants.

	MADRES (N=213)	**S1** (N=500)	**S2** (N=500)	**S3** (N=500)	**S4** (N=500)	**S5** (N=500)
Age (years) - Mean (SD)	28.3 (6.00)	32.3 (8.26)	32.3 (8.26)	32.4 (8.25)	32.4 (8.25)	32 (8.42)
Race - n (%)						
White, non-Hispanic	12 (5.6%)	89 (17.8%)	89 (17.8%)	115 (23.0%)	115 (23.0%)	127 (25.4%)
Asian, non-Hispanic	2 (0.9%)	87 (17.4%)	87 (17.4%)	62 (12.4%)	62 (12.4%)	73 (14.6%)
African American, non-Hispanic	24 (11.3%)	51 (10.2%)	51 (10.2%)	45 (9.0%)	45 (9.0%)	39 (7.8%)
Hispanic	169 (79.3%)	257 (51.4%)	257 (51.4%)	266 (53.2%)	266 (53.2%)	247 (49.4%)
Other	6 (2.8%)	16 (3.2%)	16 (3.2%)	12 (2.4%)	12 (2.4%)	14 (2.8%)

Estimated times spent in various microenvironments were similar across APEX scenarios (Table S4.2). Figure 4.2a shows that individuals spent the majority of their time indoors in *S3*.

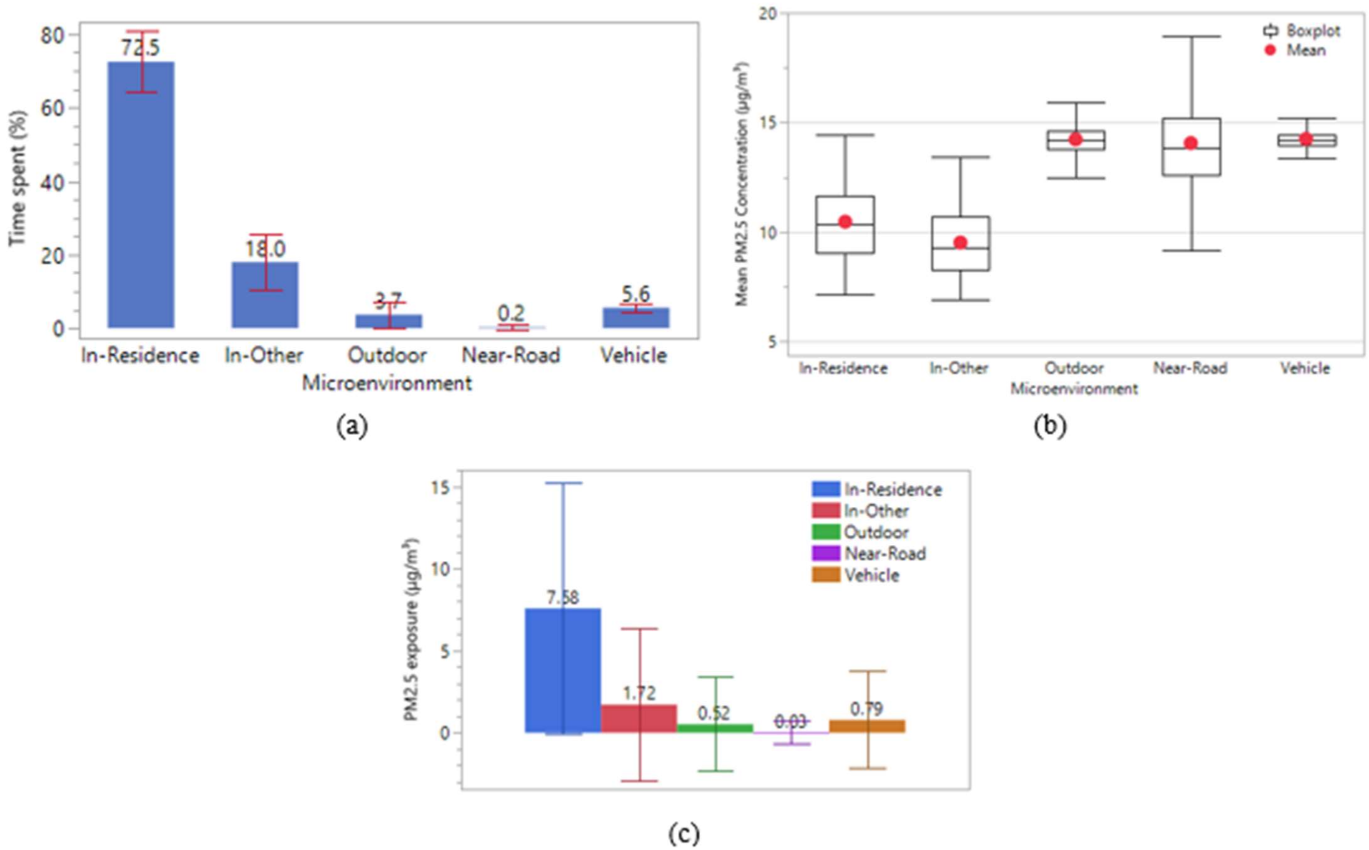

Figure 4.2. APEX scenario *S3* simulated results by microenvironment for: (a) stay time durations (%); (b) $PM_{2.5}$ concentrations (µg/m^3); and (c) Personal time-weighted $PM_{2.5}$ exposures (µg/m^3) (*Numbers indicate means and error bars indicate standard deviations)

APEX simulated individuals spent 7% (SD=8) less time at home compared to MADRES participants (79%) (SD=20) and more time at other indoor locations (18% vs. 15%). Actual time-activity patterns were also more variable than APEX simulated ones.

APEX estimated $PM_{2.5}$ concentrations in Near Road, Outdoor, and Vehicle microenvironments were much higher than in the two indoor microenvironments across all five APEX scenarios (Table S4.3). In-Residence $PM_{2.5}$ concentrations increased between *S1* (mean=8.8 μg/m^3, SD=1.6), *S2* (9.8 μg/m^3, 1.5), and *S3* (10.5 μg/m^3, 1.7) due to the impact of window opening and the combined impact of window openings and indoor cooking, respectively. *S4* (9.9 μg/m^3, 1.6) integrated indoor candle or incense burning, while *S5* (10.4 μg/m^3, 1.7) combined both indoor sources of cooking and indoor candle or incense burning. Through comparing how well these scenarios reproduced personal measurements, *S3* was the optimal one given it had the best approximation to personal measurements (with the highest mean value among scenarios), followed by *S5* with similar estimates. Using *S3* results as an example, the time spent in both indoor microenvironments was higher than the others (Figure 4.2a); both indoor microenvironmental $PM_{2.5}$ concentrations were lower than the others (Figure 4.2b), while time-weighted exposures in both indoor microenvironments were higher than exposures from Outdoor, Near-Road, and Vehicle microenvironments (Figure 4.2c). In-Residence microenvironment contributed most of the personal exposures (67-71% in different scenarios), followed by the exposures in In-Other (16-19%), Vehicle (7-8%), Outdoor (5-6%) and Near-Road (0.3-0.4%) on an hourly basis (Table S4.4).

Figure 4.3 shows hourly personal $PM_{2.5}$ exposures contributed by the various microenvironments throughout the day. In-residence exposures dominated the evening hours and contributed substantially during the daytime hours as well. In-Other microenvironmental exposures also had sizeable contributions between 10 a.m. and 5 p.m., during which simulated individuals were probably in work locations or other indoor environments. Vehicle and outdoor exposures had observable shares between 9 a.m. and 8 p.m., while the contributions from Near-Road were negligible all of the time.

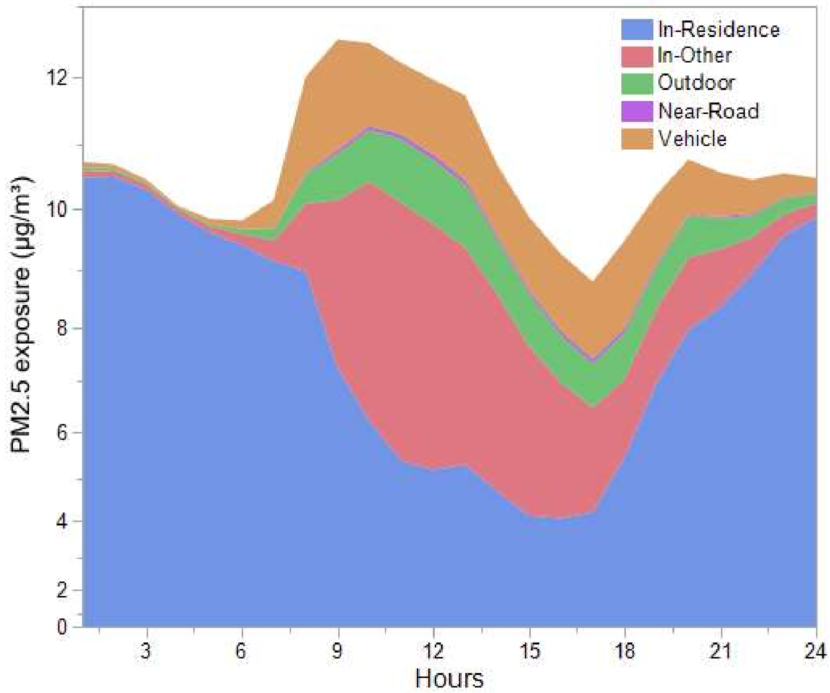

Figure 4.3. Contributions of various microenvironments to hourly personal $PM_{2.5}$ exposures in *S3* (*power scale of 1.5 used for Y-axis values)

Table 4.3 presents Spearman correlations among simulated, hourly microenvironment exposures, ambient $PM_{2.5}$ concentrations, and personal exposures from *S3*. Hourly personal exposure estimates were strongly correlated with ambient $PM_{2.5}$ concentrations (r=0.83). Personal exposures had the strongest correlation with In-Residence exposures (r=0.54). In-Residence exposures were negatively correlated with Outdoor exposures (r=-0.24), but positively correlated with ambient $PM_{2.5}$ (r=0.46). Tables S4.5 and S4.6 show similar correlations in *S1* and *S2*.

Table 4.3. Spearman correlations among simulated hourly total personal $PM_{2.5}$ exposures, microenvironmental $PM_{2.5}$ exposures, and ambient $PM_{2.5}$ concentrations in *S3*.

	Total Personal $PM_{2.5}$ Exposure	In-Residence $PM_{2.5}$	In-Other $PM_{2.5}$	Outdoor $PM_{2.5}$	Near-Road $PM_{2.5}$	Vehicle $PM_{2.5}$	Ambient $PM_{2.5}$
APEX Estimates							
In-Residence $PM_{2.5}$	**0.54**						
In-Other $PM_{2.5}$	**0.02**	**-0.65**					
Outdoor $PM_{2.5}$	**0.09**	**-0.24**	**0.10**				
Near-Road $PM_{2.5}$	**0.02**	**-0.07**	**-0.002**	**0.04**			
Vehicle $PM_{2.5}$	**0.11**	**-0.29**	**0.28**	**0.32**	**0.07**		
Ambient $PM_{2.5}$	**0.83**	**0.46**	**0.05**	**0.004**	**-0.003**	**0.02**	

Values in bold font represent significant p-values at $p<0.05$ level.

Overall mean MADRES personal $PM_{2.5}$ measurements were almost twice as high as mean ambient concentrations at monitoring stations and two or more times higher than the APEX personal exposure estimates (Table 4.4). In addition, 48-hr integrated MADRES measured exposures were more variable than daily APEX estimates.

Table 4.4. $PM_{2.5}$ comparisons among MADRES personal measurements, APEX estimates, and USEPA monitoring station concentrations ($\mu g/m^3$).

	$PM_{2.5}$ Concentrations ($\mu g/m^3$)						
	Personal measurements	APEX estimates					Ambient concentrations
		S1	S2	S3	S4	S5	
Minimum	1.8	0.1	0.1	0.2	0.1	0.3	0
Maximum	140.2	111.1	114.1	112.8	123.5	117.5	121.0
Mean (SD)	23.3 (19)	9.5 (5)	10.2 (6)	10.7 (6)	10.2 (6)	10.6 (5)	11.7 (7)

Sensitivity analyses were also conducted to test the impact of including non-MADRES residential tracts on estimated personal $PM_{2.5}$ exposures. Compared to the simulated individuals living in the non-MADRES census tracts, the individuals within the MADRES census tracts had slightly higher exposures (0.3-2.4% higher in different scenarios). Most of simulated Hispanic women (i.e., 247-266 out of 500 simulated individuals) had significantly lower exposures compared to MADRES Hispanic participants (i.e.,169 out of 213 individuals included in this comparison).

4.4. Discussion

In this study, personal $PM_{2.5}$ exposures were simulated for 500 individuals randomly selected to represent the larger population of women of child-bearing age living in Los Angeles, CA, from October 1, 2016 to March 11, 2020. The simulated exposures were compared with the personal measurements in a sub-study of 213 women enrolled in the MADRES study. Although MADRES participants represent an imperfect sample of the simulated population, this study provided a unique opportunity to examine whether the APEX model could estimate the range of personal exposures for a larger environmental health disparities population from which the MADRES cohort is drawn. Furthermore, by comparing model estimates within microenvironments to personal measurements, the evaluation can be made to see whether more nuanced inputs can generate estimated exposures closer to the distribution of the real exposures and capture the complexity in total personal exposure.

The results show that the estimated personal $PM_{2.5}$ exposures were significantly lower than MADRES personal measurements, indicating that the model underestimated personal exposures. Personal exposures are modelled as time-weighted averages of microenvironmental $PM_{2.5}$ concentrations which integrate both time-activities of individuals and pollutant concentrations in each microenvironment (Duan 1982; Johnson et al., 2018; Sarnat S.E. et al., 2013). This study gathered and used the microenvironmental parameters from Johnson et al. (2018) to calculate microenvironmental $PM_{2.5}$ concentrations and encountered the same issues documented by Johnson et al. (2018). The lack of knowledge about one or more critical parameters (e.g., AER, decay rates, emission rates) determining indoor concentrations may result in the underestimation of microenvironment concentrations.

The results also show strong correlations between APEX personal exposure estimates and ambient $PM_{2.5}$ (Spearman r=0.83), while the parallel correlation between personal measurements and outdoor $PM_{2.5}$ concentrations at residence (r=0.09) was fairly low among MADRES participants. This large difference indicates that APEX estimates are perhaps mostly driven by $PM_{2.5}$ sources of outdoor origin. APEX estimates might not be fully capturing the complexity of personal exposures including indoor $PM_{2.5}$ sources, the role of personal behaviors, individual activities, and home characteristics. Nonetheless, this also points to ways to refine the model inputs and improve personal exposure estimates. Given that indoor cooking and window opening behaviors were common among MADRES participants, the parameters that reflected these behaviors were added to the scenarios, and this improved the ability of the model outputs approximate to personal measurements. This result suggested ways to fine-tune the APEX parameters so the model can better describe the exposures of populations of special interest like in this dissertation.

Compared to the small subset of MADRES participants, APEX underestimated durations of staying at home for simulated individuals. Previous studies have shown that the durations of staying in microenvironments, particularly indoor at residence, is an important factor affecting total personal exposure occurring indoors (Adgate et al., 2004b; Jenkins et al., 1992; Kim et al., 2005; Turpin et al., 2007). In this study, the CHAD California data was used to generate activity diaries for simulated individuals. The majority of the CHAD data specifically describing activities for Californians was collected between 1987 and 1992 (McCurdy et al., 2000). Even though several activity studies were incorporated into the original CHAD in November 2016, the most recent study was conducted from 2003 through 2011 (Graham et al., 2019). In addition, among 23 studies incorporated in CHAD, only two studies were conducted in the Los Angeles area with real-time diaries collected from students aged 10 to 17 years (Graham et al., 2019). Given the CHAD data might be outdated, the activity diaries used by APEX might not represent current day time-activities for individuals. The differences of spatial range for study areas, age range of respondents, and the type of survey designs used in the CHAD and MADRES studies, along with the specific time-activity patterns for pregnant women, might also contribute to the time duration spent in microenvironments differences between APEX individuals and MADRES participants. Therefore, the inclusion of more recent and representative diary data for the specified study area, age and socioeconomic range, even for a special population group such as pregnant women in CHAD datasets may produce estimates that better approximate personal measurements in a similar future study.

While APEX provides some flexibility in terms of capturing the characteristics of the population at hand, there are still some areas that would benefit from further customization. For example, the default microenvironment setting does not provide the option to set up different home characteristics (e.g., living in an apartment or a house) for In-Residence among simulated individuals; however, around 60% of MADRES participants live in an apartment while 40% live in a house. Some studies have shown that air exchange rates (AER) can be twice as high for apartments compared to single-family homes in certain contexts (Price et al., 2006). This means that there may be important differences in In-Residence exposures for apartments and for houses, and that we might define multiple In-Residence settings accordingly. In terms of multiple $PM_{2.5}$ sources that could influence personal exposures, such as secondhand smoking which happens across several microenvironments (Fabian et al., 2016; Zamora et al., 2018), the current model setting does not seem to allow specifying such conditions very well.

The strength of this research included applying APEX to model personal exposures for the population with pre-defined microenvironments and multiple emission sources. The outputs improve our understanding of personal exposures at the microenvironment level. Furthermore, the results reveal the need for the refinement of the model inputs to reproduce the distribution of personal measurements. One limitation is that the MADRES sub-study participants with personal monitoring are an imperfect subset of the larger MADRES cohort, which in itself is an imperfect (in statistical terms) of the sample drawn from the larger environmental health disparities population we aimed to simulate with APEX. In addition, the lack of sufficient knowledge regarding the distributions of model parameters, as well as indoor emission sources within microenvironments in our own data, affected our ability to model personal $PM_{2.5}$ exposures.

4.5. Conclusion

The research findings show that the APEX model does a great job at modeling personal exposure to $PM_{2.5}$ of outdoor origin. It demonstrates a much greater improvement compared to just relying on outdoor data, since it incorporates ventilation conditions and allows changes in ventilation (e.g., open windows and air conditioner usage) based on actual temperature. However, it seems more involved or complex to try to recreate all the different sources that contribute to total personal exposure than is currently possible using APEX. The results may lead to a better understanding of how the APEX model can be used to estimate personal $PM_{2.5}$ exposures, along with potential improvements in input specifications to better approximate personal exposures.

Chapter 5 Conclusions

Exposure to air pollution and $PM_{2.5}$ more specifically is an important environmental risk factor that has been associated with various adverse health outcomes. Pregnancy in particular is considered a sensitive exposure window with potential for long term impacts on maternal and child health. Systemic inequities over time lead to persistent environmental health disparities, which result in disadvantaged groups such as the low-income Hispanic population in Los Angeles being disproportionally exposed to air pollution and more susceptible to its health risks. Personal exposure to $PM_{2.5}$ is complex, as $PM_{2.5}$ itself is a mixture of various sources with varying physicochemical properties and toxicity that could contribute to varying health outcomes. Human mobility, time-activity patterns, and behaviors may also contribute to variations of personal exposure.

Most health studies rely on outdoor $PM_{2.5}$ estimates to investigate the associated health outcomes, assuming they are the best surrogate of personal $PM_{2.5}$ exposure of outdoor origin. However, ignoring the impacts of factors such as activity spaces and time-activities on personal exposure might result in exposure measurement error. In addition to the health risks of outdoor $PM_{2.5}$, understanding the effects of total personal $PM_{2.5}$ exposures and indoor exposure specifically is increasingly important given their high contribution to personal exposures and their potential impacts on health. To date, knowledge around understanding personal $PM_{2.5}$ exposures of low-income Hispanic pregnant women has been limited due to the complexity of the sources contributing to their personal exposures, the multitude of co-occurring risk factors in this sensitive window of time, and the greater systemic disadvantages they experience.

In this dissertation, personal $PM_{2.5}$ measurements and concurrent geolocation records for a population of low-income, predominantly Hispanic pregnant women provided a unique opportunity to fill this gap. Three aspects of their personal exposures were examined in three separate studies. Study 1 was focused on investigating the main determinants, e.g., environmental exposures within GPS-derived activity spaces, time-activity patterns, indoor sources, etc. and their impacts on personal exposures. Study 2 was focused on investigating the main sources and their contributions to personal $PM_{2.5}$ mass distinguished based on their chemical fingerprints. Study 3 examined the contribution of microenvironments to personal exposures and whether total personal exposure could be estimated for larger populations using a well-known and population stochastic inhalation exposure model.

The results from Study 1 revealed a direct association between greater green cover and parks and open space exposure in activity spaces and lower personal $PM_{2.5}$ exposure which has not been reported in previous studies. In addition, compared to the impact of outdoor residential $PM_{2.5}$, indoor $PM_{2.5}$ sources and indoor activities had a greater contribution to personal exposure (on a standard deviation scaled basis). Study 2 identified six main sources based on their chemical fingerprints that contributed to total personal $PM_{2.5}$ mass concentration, with combined indoor source contributions greater than three times those of outdoor sources. The APEX inhalation model results from Study 3 captured the contribution of outdoor $PM_{2.5}$ to personal exposure, since predicted total personal exposure was highly correlated with outdoor $PM_{2.5}$, contrary to the weak correlation observed when using personal measurements. However, the Indoor-Residence microenvironment contributed the majority of estimated personal exposures. Overall, the model seemed to underestimate total personal exposures when compared to personal measurement data despite the addition of different combinations of indoor source emission terms selected based on the most commonly reported or observed sources in earlier studies. Refinement of inputs such as more accurate indoor source terms and current time-activity budgets that represent environmental health disparities populations would likely yield improved personal exposure estimates.

Taken together, the findings of the three studies characterize personal $PM_{2.5}$ exposures of the low-income, predominantly Hispanic pregnant women. The results point to the significant impact of GPS-derived activity spaces on the variation of personal exposures. Compared to residential neighborhoods, environmental exposures within activity spaces, particularly KDE area, are more correlated with where and how individuals interacted with their environments. Therefore, using activity spaces may detect the associations between built-environment and personal $PM_{2.5}$ exposures in more accurate ways (e.g., greenness within KDE). This also reveals the possible exposure measurement error when outdoor $PM_{2.5}$ estimates at the residence are used to approximate personal exposures of outdoor origin in health studies. This quantification of environmental impacts could, in turn, facilitate the design of potential interventions, e.g., promoting "greener" urban spaces from the policy and practice perspective.

Similarly, the results for indoor candle or incense burning, duration of staying indoors, indoor activities and home ventilation (Study 1), sources of secondhand smoking and crustal (Study 2), and major contribution of Indoor-Residence exposure (Study 3), show the significant contributions to total personal exposures across all three investigations. The identified sources and factors reveal the importance of indoor environment when assessing personal $PM_{2.5}$ exposures, which also improve our understanding of the disproportional exposures that this low-income Hispanic population burdened. In addition to regulating outdoor $PM_{2.5}$ concentrations, interventions or standards that target the indoor environment, e.g., reducing indoor $PM_{2.5}$ emissions or requiring building designers and operators to increase removal of indoor $PM_{2.5}$, need to be developed in a scientific, evidence-based manner to provide adequate health protection. This finding also raises the awareness to examine the health effects of the source-specific $PM_{2.5}$ exposures, given the varied species and toxicity related to each source and the fact that individuals are exposed to these mixtures and not a single pollutant or chemical at a time.

Lastly, the results demonstrate the possibility of using modeling approaches to estimate personal exposures, particularly the personal exposures of outdoor origin. However, with the significant contributions of indoor sources on personal measurements, more work needs to be accomplished to model indoor microenvironment exposures from non-outdoor sources (e.g., emission from indoor $PM_{2.5}$ sources or human activities), which may improve personal exposure predictions accordingly. To facilitate modeling $PM_{2.5}$ concentrations of the indoor microenvironments, a database of indoor source emission distributions, as well as a library of home ventilation effects on AER distributions, under wide ranging conditions that represent a diverse population would make a significant contribution to this field. In addition, more recent and representative travel and activity diary data covering a wide range of geographies, age and socioeconomic status (SES) are recommended to be included in the CHAD or similar national time-activity and travel behavior datasets, which may result in the improved estimates of time spent in each microenvironment. Integrating SES information into population data for modeling will make it possible to refine simulations, which may further improve exposure predictions for individuals that are part of environmental health disparities populations. These tangible recommendations, combined with modeling exposure of outdoor origin, may provide an actionable way for improved personal exposure prediction in large populations and over longer periods of time, which might greatly reduce the cost and burden of understanding personal exposures. Collecting personal exposure measurements in tailored and targeted assessments;

however, can provide important validation data to continuously improve models and achieve a greater understanding of personal exposures of different populations at scale.

My research demonstrates the complexity of how this pregnant environmental health disparities population get exposure to $PM_{2.5}$, and my findings provide foundation to refine source-specific estimates of personal exposure to $PM_{2.5}$ of outdoor origin and total personal $PM_{2.5}$. By doing so may reduce exposure measurement error, which these more accurate exposure estimates can help epidemiological health studies. The greenness finding reveal the direct link between urban design, city planning, and greener activity spaces on reducing personal exposures, which may improve public health. In addition, my results also reveal the need for smarter, more contextually aware interventions targeting main sources and determinants, particularly indoor environment due to its significant contribution on total exposures. The research also demonstrate the importance of interdisciplinary approach, or collaboration of multiple disciplines, e.g., geography, exposure sciences, urban planning, public health, and demography, to understand the complexity of personal $PM_{2.5}$ exposure for this particular population.

As the strength of my research, to my knowledge, this is one of the very few studies that conducted a thorough investigation on personal $PM_{2.5}$ exposures of predominantly Hispanic and low-income women during pregnancy in an environmental health disparities context. The personal $PM_{2.5}$ monitoring and concurrent GPS data constitute a rich dataset which enabled this investigation. In terms of the generalizability of my research, some of my findings, e.g., greenness and traffic impact, indoor sources, and outdoor PM can be generalizable to other urban areas and other population; and the ways of approaching it may be transferable to other environmental health disparities contexts and studies. As for the limitations, the sample size of

200 might be considered low, however for personal monitoring studies that are quite expensive and burdensome to conduct to provide the highest quality data, this is considered fairly decent. Of course, if it weren't for the pandemic we would have expected a slightly larger sample size.

Overall, the dissertation findings help to dissect the complexity of personal $PM_{2.5}$ exposures of this susceptible low-income predominantly Hispanic population during the critical window of pregnancy. These findings can be further applied to advance environmental health research and recommend appropriate interventions with the aim to control or minimize personal $PM_{2.5}$ exposures, which may further reduce health disparities.

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Appendix A

Table S2.1. Summary of personal monitoring data collection time for MADRES participants.

Year	Month												N (%)
	January	February	March	April	May	June	July	August	September	October	November	December	
	N	N	N	N	N	N	N	N	N	N	N	N	
2016	0	0	0	0	0	0	0	0	0	3	1	4	8 (3.8%)
2017	1	2	0	3	2	7	6	7	9	3	2	3	45 (21.1%)
2018	2	2	2	2	3	4	5	2	1	4	12	7	46 (21.6%)
2019	11	12	6	3	9	8	6	12	10	9	6	5	97 (45.5)
2020	8	5	4	0	0	0	0	0	0	0	0	0	17 (8.0%)
N (%)	22 (10.3%)	21 (9.9%)	12 (5.6%)	8 (3.8%)	14 (6.6%)	19 (8.9%)	17 (8.0%)	21 (9.9%)	20 (9.4%)	19 (8.9%)	21 (9.9%)	19 (8/9%)	213 (100%)

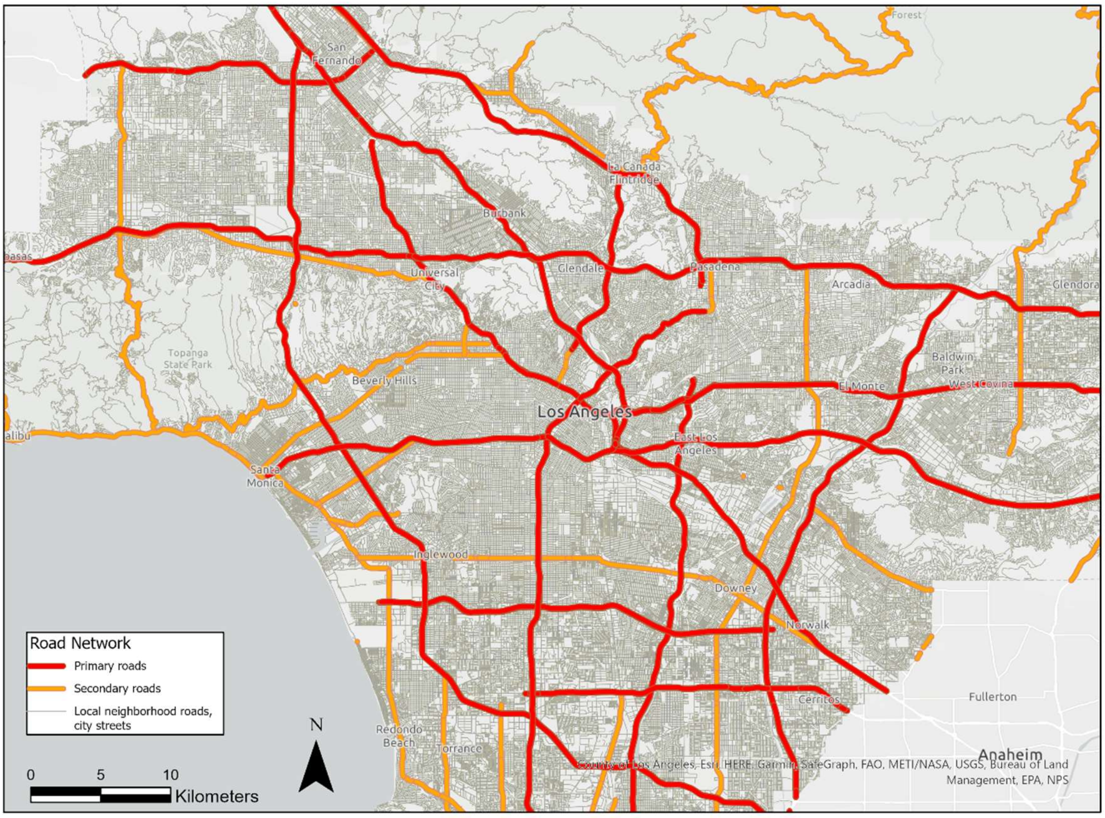

Figure S2.1. Los Angeles, CA, primary, secondary, and local neighborhood roads and city streets used in the analysis

Table S2.2. Personal sampler wearing compliance (N=213).

	N (%)
Wear compliance while awake during the daytime	
Missing	1 (0.5%)
none	10 (4.7%)
medium	10 (4.7%)
high	192 (90.1%)
Wear compliance while sleeping during the nighttime	
Missing	1 (0.5%)
none	16 (7.5%)
medium	13 (6.1%)
high	183 (85.9%)
Place nearby when not worn it during the daytime	
Missing	1 (0.5%)
none	7 (3.3%)
medium	5 (2.3%)
high	200 (93.9%)

Table 2.3. The distribution of personal and outdoor (residential and selected activity spaces) $PM_{2.5}$ mass concentrations (µg/m^3).

	N	Mean (SD)	Min	Median	Max
Personal $PM_{2.5}$	213	23.3 (18.9)	1.8	18.4	140.2
Outdoor $PM_{2.5}$					
At residential location	209	11.8 (5.5)	2.9	10.9	35.1
Within MCH area	199	11.3 (5.5)	0.5	10.7	33.8
Within DPA	199	11.3 (5.5)	0.5	10.7	33.6
Within KDE area (K10/100m)	199	11.4 (5.5)	0.5	10.6	33.7
Within (K25/250m)	199	11.4 (5.5)	0.5	10.7	33.7
Within KDE area (K50/500m)	199	11.4 (5.5)	0.5	10.7	33.6

*MCH: minimum convex hull, DPA: daily path area, KDE: kernel density estimation

Table S2.4. Bivariate relationships between personal $PM_{2.5}$ exposures and questionnaire variables.

Variables	N (%)	Mean (SD)	*p*-value	Variables	N (%)	Mean (SD)	*p*-value
Time-Activity				*Home carpeting			**0.03**
**Time spent outdoors			0.07	No	106 (49.8%)	26.4 (22.1)	
None or a little of time	135 (63.4%)	21.6 (17.5)		Yes	92(43.2%)	20.2 (15.3)	
Most or all of time	77 (36.1%)	25.3 (19.9)		Missing	15 (7.0%)	19.8 (8.4)	
Missing	1 (0.5%)	86.1 (-)		**Air conditioner used at home			0.12
**Outdoor and near traffic			0.10	None of the time	157 (73.7%)	23.3 (18.1)	
No	82 (38.5%)	20.2 (13.6)		A little, most, or all of the time	55 (25.8%)	22.1 (19.5)	
Yes	130 (61.0%)	24.7 (20.8)		Missing	1 (0.5%)	86.1 (-)	
Missing	1 (0.5%)	86.1 (-)		**Indoor Sources of Air Pollution**			
**Maximum commuting time			0.25	**Time close to smoke from candles or incense burning nearby			**0.03**
0 to 30 min	56 (26.3%)	23.4 (16.2)		None of the time	160 (75.1%)	21.6 (17.7)	
30 min to 1 hr	47 (22.1%)	27.6 (27.6)		A little, most, or all of the time	52 (24.4%)	27.2 (20.0)	
1 to 2 hrs	39 (18.3%)	25.5 (17.9)		Missing	1 (0.5%)	86.1 (-)	
> 2 hrs	41 (19.2%)	17.3 (7.4)		*Average stove use time at home			0.19
Missing	30 (14.1%)	21.2 (17.7)		Less than 30 min	40 (18.8%)	18.7 (10.8)	
Home Characteristics				30 min or more	139 (65.2%)	24.1 (19.9)	
*Home type			**0.004**	Missing	34 (16.0%)	25.3 (21.7)	
House	75 (35.2%)	19.4 (16.5)		**Time close to cigarette, cigar, hookah or pipe smoke from people smoking nearby			0.36
Apartment	122 (57.3%)	26.1 (20.8)		None of the time	128 (60.1%)	22.9 (17.2)	
Missing	16 (7.5%)	19.8 (8.1)		A little, most, or all of the time	83 (39.0%)	23.2 (20.3)	

**Window open time			0.14	Missing	2 (0.9%)	48.6 (53.0)	
None or a little of time	85 (39.9%)	26.3 (23.9)		**Demographics**			
Most or all of time	127 (59.6%)	20.7 (13.2)		*Education level			**0.05**
Missing	1 (0.5%)	86.1 (-)		Less than 12th grade	51 (24.0%)	26.7 (23.0)	
*Number of people living in a household			0.07	Completed grade 12	65 (30.5%)	21.5 (13.1)	
1 to 2 people	26 (12.2%)	19.8 (12.4)		Some college	63 (29.6%)	26.2 (23.1)	
3 people	30 (14.1%)	26.4 (18.5)		College and above	32 (15.0%)	15.8 (7.4)	
4 people	40 (18.8%)	19.8 (12.2)		Missing	2 (0.9%)	21.0 (14.7)	
5 people	20 (9.4%)	22.4 (18.3)		*Parity			0.07
> 5 people	35 (16.4%)	29.4 (22.3)		1	71 (33.3%)	19.6 (13.0)	
Missing	62 (29.1%)	22.2 (22.2)		2	62 (29.1%)	21.9 (19.1)	
*Home built year			0.49	>2	72 (33.8%)	28.3 (22.9)	
After 1980s	91 (42.7%)	22.8 (19.0)		Missing	8 (3.8%)	21.2 (12.9)	
Before 1980s	69 (32.4%)	24.2 (18.9)					
Missing	53 (24.9%)	22.9 (19.0)					

* From the 3rd trimester questionnaire; ** Reported or derived from exit survey referring to 48-hour monitoring period.
Values presented in bold font shows significant p-values at $p<0.05$ level.

Table S2.5. Bivariate association between primary road lengths within activity spaces and residential neighborhoods with personal $PM_{2.5}$ exposure (N=213).

Length of Primary Roads (m) by Method	**Mean (SD)**	**Spearman Correlation**	**p-value**
Activity Space			
Daily Path Area (DPA)	80,163.8 (121,844.5)	0.02	0.817
Minimum Convex Hull (MCH)	108,645.0 (239,961.7)	-0.04	0.605
Kernel Density Estimation (KDE) measures (bin size, neighborhood size)			
10 m, 100 m	6.2 (17.5)	0.02	0.802
10 m, 100 m, top 20th percentile	12,736.9 (29,165.6)	-0.01	0.885
10 m, 250 m	12.7 (36.0)	0.12	0.085
10 m, 250 m, 20th percentile	18,026.6 (40,688.9)	0.01	0.836
25 m, 250 m	79.7 (226.5)	0.13	0.073
25 m, 250 m, 20th percentile	17,993.2 (40,590.0)	0.02	0.775
25 m, 500 m	106.4 (216.7)	0.11	0.112
25 m, 500 m, 20th percentile	20,884.9 (44,589.5)	0.08	0.291
50 m, 500 m	425.7 (865.9)	0.12	0.094
50 m, 500 m, 20th percentile	20,847.9 (44,508.5)	0.07	0.331
Residential Neighborhood			
Residential census tract (RN_ct)	1,309.6 (2,508.8)	-0.04	0.516
100 m buffer around residence (RN_100 m)	4.5 (47.9)	0.05	0.477
250 m buffer around residence (RN_250 m)	208.3 (644.2)	0.10	0.140
500 m buffer around residence (RN_500 m)	1,266.3 (2,168.4)	0.07	0.340

Table S2.6. Spearman correlations of total primary road lengths within activity spaces and residential neighborhoods, colored from low (blue) to high (red) (N=213).

	DPA	MCH	K10/100m	K10/100m$_{20p}$	K10/250m	K10/250m$_{20p}$	K25/250m	K25/250m$_{20p}$	K25/500m	K25/500m$_{20p}$	K50/500m	K50/500m$_{20p}$	RN_ct	RN_100m	RN_250m
DPA															
MCH	**0.97**														
K10/100m	**0.91**	**0.89**													
K10/100m$_{20p}$	**0.95**	**0.95**	**0.92**												
K10/250m	**0.81**	**0.75**	**0.88**	**0.78**											
K10/250m$_{20p}$	**0.96**	**0.94**	**0.92**	**0.97**	**0.83**										
K25/250m	**0.81**	**0.75**	**0.88**	**0.78**	**1**	**0.83**									
K25/250m$_{20p}$	**0.96**	**0.94**	**0.92**	**0.97**	**0.83**	**1**	**0.83**								
K25/500m	**0.66**	**0.56**	**0.67**	**0.57**	**0.85**	**0.64**	**0.85**	**0.64**							
K25/500m$_{20p}$	**0.95**	**0.92**	**0.89**	**0.93**	**0.84**	**0.97**	**0.84**	**0.97**	**0.7**						
K50/500m	**0.66**	**0.56**	**0.67**	**0.57**	**0.85**	**0.64**	**0.85**	**0.64**	**1**	**0.7**					
K50/500m$_{20p}$	**0.95**	**0.92**	**0.89**	**0.93**	**0.84**	**0.97**	**0.84**	**0.97**	**0.71**	**1**	**0.71**				
RN_ct	0.14	0.07	0.14	0.11	**0.3**	**0.14**	**0.3**	**0.14**	**0.49**	**0.18**	**0.49**	**0.19**			
RN_100m	-0.02	-0.05	**0.17**	-0.005	**0.17**	0.004	**0.17**	0.004	**0.16**	-0.003	**0.16**	-0.01	**0.18**		
RN_250m	0.11	0.05	**0.19**	**0.1**	**0.46**	**0.14**	**0.47**	**0.14**	**0.52**	**0.18**	**0.52**	**0.18**	**0.59**	**0.29**	
RN_500m	**0.24**	**0.16**	**0.25**	**0.17**	**0.42**	**0.22**	**0.42**	**0.22**	**0.7**	**0.3**	**0.7**	**0.31**	**0.71**	**0.19**	**0.64**

Values presented in bold font show significant p-values at p<0.05 level.

Table S2.7. Associations between personal $PM_{2.5}$ and NDVI within activity spaces and residential neighborhood.

	Variables	**Spearman Correlation**	***p*-value**
Residential Neighborhood	Residence, 100 m buffer	-0.05	0.429
	Residence, 250 m buffer	0.01	0.911
	Residence, 500 m buffer	0.04	0.605
	Residence, census tract	0.01	0.914
Activity Space -DPA	Daily Path Area	-0.1	0.172
Activity Space -MCH	Minimum Convex Hull	-0.03	0.710
Activity Space - KDE (20p)	KDE, 10m, 100m, 20p	-0.12	0.084
	KDE, 10m, 250m, 20p	-0.12	0.104
	KDE, 25m, 250m, 20p	-0.11	0.112
	KDE, 25m, 500m, 20p	-0.08	0.250
	KDE, 50m, 500m, 20p	-0.05	0.464
Activity Space - KDE	KDE, 10m, 100m	-0.03	0.644
	KDE, 10m, 250m	-0.01	0.924
	KDE, 25m, 250m	**-0.15**	0.037
	KDE, 25m, 500m	-0.04	0.550
	KDE, 50m, 500m	-0.02	0.802

Values presented in bold font show significant p-values at p<0.05 level

Table S2.8. Spearman correlations of average NDVI within activity spaces and residential neighborhoods, colored from low (blue) to high (red).

	DPA	MCH	K10/100m	K10/100m 20p	K10/250m	K10/250m 20p	K25/250m	K25/250m 20p	K25/500m	K25/500m 20p	K50/500m	K50/500m 20p	RN_ct	RN_100m	RN_250m
DPA															
MCH	0.80														
K10/100m	0.50	0.41													
$K10/100m_{20p}$	0.63	0.59	0.50												
K10/250m	0.59	0.45	0.82	0.54											
$K10/250m_{20p}$	0.75	0.62	0.53	0.90	0.65										
K25/250m	0.50	0.43	0.65	0.53	0.76	0.55									
$K25/250m_{20p}$	0.72	0.60	0.52	0.85	0.66	0.95	0.54								
K25/500m	0.58	0.47	0.57	0.46	0.74	0.54	0.87	0.52							
$K25/500m_{20p}$	0.79	0.64	0.53	0.80	0.69	0.91	0.59	0.88	0.61						
K50/500m	0.51	0.42	0.53	0.42	0.67	0.48	0.84	0.47	0.92	0.52					
$K50/500m_{20p}$	0.77	0.62	0.51	0.74	0.65	0.84	0.54	0.85	0.58	0.90	0.50				
RN_ct	0.52	0.39	0.55	0.37	0.69	0.47	0.53	0.48	0.59	0.51	0.52	0.53			
RN_100m	0.42	0.25	0.75	0.34	0.74	0.42	0.54	0.43	0.51	0.43	0.51	0.44	0.68		
RN_250m	0.50	0.31	0.61	0.38	0.81	0.50	0.60	0.51	0.66	0.57	0.58	0.54	0.82	0.79	
RN_500m	0.59	0.40	0.59	0.41	0.74	0.52	0.56	0.51	0.68	0.59	0.59	0.58	0.86	0.71	0.90

Values presented in bold font show significant p-values at p<0.05 level

Table S2.9. Associations between personal $PM_{2.5}$ and park area (mean and sum) within activity spaces and residential neighborhoods.

Variables (mean area)	Spearman Correlation	p-value	Variables (sum area)	Spearman Correlation	p-value
Residence, 100 m buffer	0.03	0.71	Residence, 100 m buffer	0.03	0.71
Residence, 250 m buffer	0.1	0.16	Residence, 250 m buffer	0.1	0.15
Residence, 500 m buffer	0.08	0.22	Residence, 500 m buffer	0.08	0.26
Residence, census tract	0.01	0.93	Residence, census tract	0.01	0.94
Daily Path Area	-0.06	0.39	Daily Path Area	-0.06	0.42
Minimum Convex Hull	-0.06	0.39	Minimum Convex Hull	-0.05	0.47
KDE, 10m, 100m, 20p	0.1	0.17	KDE, 10m, 100m, 20p	0.03	0.70
KDE, 10m, 250m, 20p	0.07	0.36	KDE, 10m, 250m, 20p	0.004	0.95
KDE, 25m, 250m, 20p	0.07	0.36	KDE, 25m, 250m, 20p	0.002	0.98
KDE, 25m, 500m, 20p	0.0003	1.00	KDE, 25m, 500m, 20p	-0.03	0.66
KDE, 50m, 500m, 20p	0.002	0.98	KDE, 50m, 500m, 20p	-0.03	0.66
KDE, 10m, 100m	0.08	0.28	KDE, 10m, 100m	0.05	0.50
KDE, 10m, 250m	0.1	0.18	KDE, 10m, 250m	0.08	0.25
KDE, 25m, 250m	0.09	0.19	KDE, 25m, 250m	0.08	0.25
KDE, 25m, 500m	0.06	0.41	KDE, 25m, 500m	0.08	0.28
KDE, 50m, 500m	0.06	0.41	KDE, 50m, 500m	0.08	0.28

Table S2.10. Summary of scaled parameter estimates for continuous variables in the final model.

Effect	Scaled Estimate	*p*-value	Model Estimate	Std Scale
Birth order of index child at time of pregnancy	5.81	<.0001	4.689	1.24
Length of primary road within KDE area (K50/500m)	2.82	0.018	0.003	865.86
Average NDVI value within KDE area (K25/250m)	-3.09	0.01	-0.239	12.92
Outdoor $PM_{2.5}$ concentration at residence	2.05	0.092	0.372	5.50
Mean length of secondary road within DPA	5.57	0.001	0.009	613.54
Mean park area within DPA	-3.62	0.009	-0.0001	59,052.13
Mean length of minor streets within RN_500 m	-2.53	0.04	-0.025	102.65

Table S2.11. Duration of time spent in each microenvironment (%) (N=199).

	Min	Max	Median	Mean	Std
Indoor	0	100	96.3	94.2	8.5
At home	0	100	81.0	78.9	18.8
Not at home	0	77.2	11.2	15.2	15.6
Outdoor	0	28.4	3.7	5.3	5.1

Appendix B

Table S3.1. Home characteristics, indoor source, and time-activities derived from questionnaires and exit survey (N=212).

Variables	n (%)
Home Characteristics	
*Which best describes the home in which you currently live most of the time?	
House	75 (35.4%)
Apartment	118 (55.7%)
Missing	19 (9.0%)
*How many people counting yourself live in your household?	
1 and 2 people	26 (12.3%)
3 people	29 (13.7%)
4 people	40 (18.9%)
5 people	20 (9.4%)
More than 5 people	34 (15.9%)
Missing	63 (29.7%)
*About when was this home building originally built?	
Built after 1980s	90 (42.5%)
Built before 1980s	68 (32.1%)
Missing	54 (25.5%)
*Is there carpeting in your home?	
No	103 (48.6%)
Yes	91 (42.9%)
Missing	18 (8.5%)
*Do you have pets at home?	
No	134 (63.2%)
Yes	74 (34.9%)
Missing	4 (1.9%)
*Does your home have heating?	
No	73 (34.4%)
Yes	120 (56.6%)
Missing	19 (9.0%)
Home Ventilation	
** How long the window open in your home, when you were there with sampler?	
None or little of the time	82 (38.7%)
Most or all of the time	127 (59.9%)
Missing	3 (1.4%)
**How open were your windows or doors in general?	
A little to half way	86 (40.6%)
Most to all the way	92 (43.4%)
Missing	34 (16.0%)
**How much of the time was a portable or ceiling fan used in your home, when you were there with the sampler?	
None of the time	129 (60.8%)
A little, most, or all of the time	78 (36.8%)
Missing	5 (2.4%)
Indoor Air Pollution Source	
**How much of the time were you close to smoke from candles or incense burning nearby?	
None of the time	158 (74.5%)
A little, most, or all of the time	51 (24.1%)
Missing	3 (1.4%)
**How much of the time were you close to smoke or fume from cooking?	
None of the time	129 (60.8%)
A little, most, or all of the time	80 (37.7%)
Missing	3 (1.4%)
**How much of the time were you close to cigarette, cigar, hookah or pipe smoke from people smoking nearby?	
None of the time	125 (59.0%)
A little, most, or all of the time	83 (39.2%)
Missing	4 (1.9%)
Time-Activities	
**How much of the time did you spend outdoors (not commuting in a car, bus or train)?	
None or a little of the time	133 (62.7%)
Most or all of the time	76 (35.8%)
Missing	3 (1.4%)
**When outdoor, whether were you near traffic?	
No	81 (38.2%)
Yes	128 (60.4%)
Missing	3 (1.4%)
**How many hours did you spend on commute?	
0 to 30 min	17 (8.0%)
30 min to 1 hr	44 (20.8%)

**How much of the time was the air conditioner used in your home, when you were there with the sampler?		1 to 2 hrs	47 (22.2%)
None of the time	154 (72.6%)	> 2 hrs	72 (34.0%)
A little, most, or all of the time	55 (25.9%)	Missing	32 (15.1%)
Missing	3 (1.4%)		

* question from 3rd trimester questionnaire; ** question from exit survey

Table S3.2. Bootstrapping Results for base solution, final rotated Fpeak solution and model variability/error diagnostics.

Legend	
Factor 1	Traffic
Factor 2	Secondhand smoking
Factor 3	Aged sea salt
Factor 4	Fresh sea salt
Factor 5	Fuel oil
Factor 6	Crustal

Mapping of bootstrap factors to base factors (BS mapping, 100 bootstraps, 0.6 minimum correlation)							
	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Unmapped
	98	0	2	0	0	0	0
	7	69	15	6	0	1	2
	0	0	98	2	0	0	0
	0	0	0	100	0	0	0
	1	0	1	0	98	0	0
	0	0	0	0	0	100	0
Mapping of Fpeak (rotated) bootstrap factors to base factors							
	Base Factor 1	Base Factor 2	Base Factor 3	Base Factor 4	Base Factor 5	Base Factor 6	Unmapped
Boot Factor 1	100	0	0	0	0	0	0
Boot Factor 2	3	94	3	0	0	0	0
Boot Factor 3	0	0	100	0	0	0	0
Boot Factor 4	0	0	0	100	0	0	0
Boot Factor 5	0	0	0	0	100	0	0
Boot Factor 6	0	0	0	0	0	100	0
DISP Diagnostics							
Error Code:	0						
Largest Decrease in Q:	0						
%dQ:	0						
Swaps by Factor:	0	0	0	0	0	0	0
BS-DISP Diagnostics							
BS-DISP Displaced Species:	BrC						
# of Cases Accepted:	98						
% of Cases Accepted:	98%						

Largest Decrease in Q:	-9.13					
%dQ:	-0.16					
# of Decreases in Q:	0					
# of Swaps in Best Fit:	1					
# of Swaps in DISP:	1					
Swaps by Factor:	1	0	0	1	0	0

Table S3.3: PMF model results showing R^2 and normality of residuals for each species.

Species	R^2	Normal residuals?
PM mass	0.48	Yes
Carbon Species		
BC	0.16	No
BrC	0.53	Yes
ETS	0.12	No
Elements		
Al	0.5	No
Ba	0.41	Yes
Br	0.24	Yes
Ca	0.53	No
Cl	0.85	No
Co	0.33	No
Cu	0.77	Yes
Fe	0.78	Yes
K	0.13	No
Mg	0.84	Yes
Mn	0.54	Yes
Na	0.86	Yes
Ni	0.35	Yes
P	0.0001	No
Pb	0.13	No
S	0.83	No
Se	0.09	Yes
Si	0.62	Yes
Sr	0.04	No
Ti	0.7	Yes
V	0.04	No
Zn	0.3	No

Appendix C

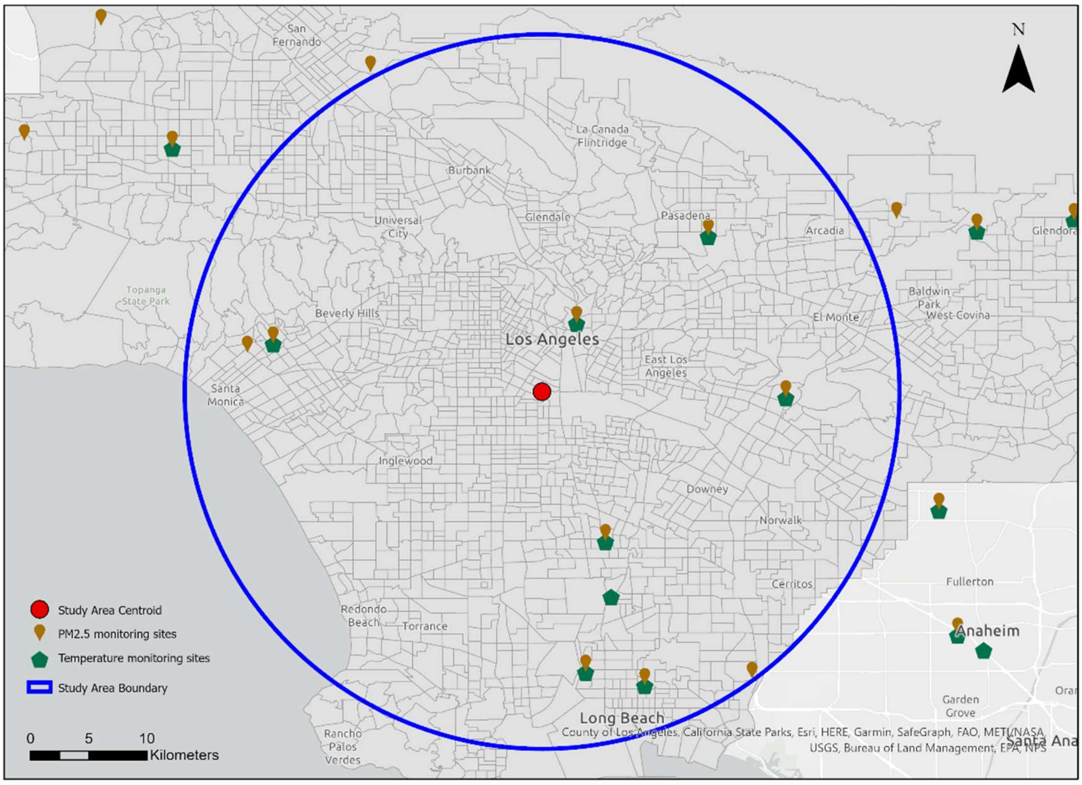

Figure S4.1. MADRES study area used for APEX model runs

Table S4.1. APEX microenvironment parameters.

Microenvironment	Parameters	Conditions	Distributions
Indoor-Residence	AER	Temp < 68; AC; room, window-open	LogN (1.344, 1.863, 0.1, 10)
		Temp 68-76; AC; room, window-open	LogN (3.348, 2.223, 0.1, 10)
		Temp > 76; AC; room, window-open	LogN (1.898, 1.644, 0.1, 10)
		Temp < 50; AC; none, window-open	LogN (1.086, 3.087, 0.1, 10)
		Temp 50-67; AC; none, window-open	LogN (1.494, 2.085, 0.1, 10)
		Temp 68-76; AC; none, window-open	LogN (2.744, 2.283, 0.1, 10)
		Temp > 76; AC; none, window-open	LogN (1.976, 1.967, 0.1, 10)
		Temp < 68; AC; room, window-close	LogN (0.672, 1.863, 0.1, 10)
		Temp 68-76; AC; room, window-close	LogN (1.674, 2.223, 0.1, 10)
		Temp > 76; AC; room, window-close	LogN (0.949, 1.644, 0.1, 10)
		Temp < 50; AC; none, window-close	LogN (0.543, 3.087, 0.1, 10)
		Temp 50-67; AC; none, window-close	LogN (0.747, 2.085, 0.1, 10)
		Temp 68-76; AC; none, window-close	LogN (1.372, 2.283, 0.1, 10)
		Temp > 76; AC; none, window-close	LogN (0.988, 1.967, 0.1, 10)
Indoor-Other	AER	All	LogN (1.109, 3.015, 0.07, 13.8)
Indoor-Residence	ES	gas stove	LogN (1700, 10, 100, 2000)
Indoor-Residence	ES	gas stove (duration)	Uniform (0.5, 1)
Indoor-Residence	Vol		Normal (120, 30, 50, 300)
Indoor-Residence	ES	candle burning	Normal (110, 60, 10, 200)
Indoor-Residence	ES	candle burning (duration)	Uniform (0.6, 1)
Indoors-All	Decay rate	All	Uniform (0.1, 1.1)
All MEs	Penetration		1
All MEs	Proximity	All	Normal (1.0, 0.07, 0.9, 1.1)

Table S4.2. Duration of time spent in each microenvironment (as a percentage per day).

Microenvironment	Mean (SD)					
	MADRES (N=213)	**S1 (N=500)**	**S2 (N=500)**	**S3 (N=500)**	**S4 (N=500)**	**S5 (N=500)**
In-Residence	78.46 (19.59)	72.06 (7.90)	72.06 (7.90)	72.50 (8.33)	72.50 (8.33)	71.79 (8.21)
In-Other	15.22 (15.66)	18.24 (7.39)	18.24 (7.39)	17.97 (7.58)	17.97 (7.58)	18.73 (7.51)
Outdoor		3.86 (3.63)	3.86 (3.63)	3.68 (3.38)	3.68 (3.38)	3.61 (3.68)
Near-Road		0.24 (0.49)	0.24 (0.49)	0.25 (0.57)	0.25 (0.57)	0.25 (0.52)
Vehicle		5.56 (1.03)	5.56 (1.03)	5.57 (1.09)	5.57 (1.09)	5.58 (1.04)

Table S4.3. Estimated mean microenvironment $PM_{2.5}$ concentrations ($\mu g/m^3$).

Microenvironments	**$PM_{2.5}$ Concentrations ($\mu g/m^3$), Mean (SD)**				
	S1	S2	S3	S4	S5
In-Residence	8.8 (1.6)	9.8 (1.5)	10.5 (1.7)	9.9 (1.6)	10.4 (1.7)
In-Other	9.7 (1.7)	9.7 (1.7)	9.5 (1.6)	9.4 (1.5)	9.5 (1.7)
Outdoor	14.2 (0.6)	14.2 (0.6)	14.2 (0.7)	14.2 (0.7)	14.3 (0.7)
Near-Road	14.1 (2.2)	14.1 (2.2)	14.1 (2.4)	14.1 (2.4)	14.1 (2.3)
Vehicle	14.2 (0.4)	14.2 (0.4)	14.2 (0.4)	14.2 (0.4)	14.2 (0.4)

Table S4.4. Estimated total personal and microenvironment $PM_{2.5}$ exposures extracted from hourly outputs ($\mu g/m^3$).

Microenvironments	**$PM_{2.5}$ Exposures, Mean (SD)**				
	S1	S2	S3	S4	S5
Estimated Personal Exposure	9.5 (7.26)	10.2 (7.63)	10.65 (7.73)	10.19 (7.69)	10.6 (7.69)
In-Residence	6.34 (6.73)	7.05 (7.39)	7.58 (7.63)	7.14 (7.46)	7.47 (7.59)
In-Other	1.77 (4.7)	1.77 (4.7)	1.72 (4.61)	1.69 (4.55)	1.79 (4.72)
Outdoor	0.55 (2.86)	0.55 (2.86)	0.52 (2.86)	0.52 (2.85)	0.51 (2.78)
Near-Road	0.03 (0.75)	0.03 (0.75)	0.03 (0.72)	0.03 (0.72)	0.04 (0.74)
Vehicle	0.79 (2.9)	0.79 (2.9)	0.79 (2.96)	0.79 (2.96)	0.79 (2.97)

Table S4.5. Spearman correlations among estimated hourly personal $PM_{2.5}$ exposures, microenvironment exposures, and ambient $PM_{2.5}$ concentrations in *S1*.

	In-Residence	In-Other	Outdoor	Near-Road	Vehicle	Ambient $PM_{2.5}$
In-Residence						
In-Other	**-0.65**					
Outdoor	**-0.24**	**0.09**				
Near-Road	**-0.07**	-0.0001	**0.03**			
Vehicle	**-0.28**	**0.28**	**0.31**	**0.07**		
Ambient $PM_{2.5}$	**0.44**	**0.05**	**0.00**	**-0.001**	**0.02**	
Personal Exposures	**0.44**	**0.12**	**0.13**	**0.03**	**0.15**	**0.81**

Values in bold font represent significant p-values at p<0.05 level.

Table S4.6. Spearman correlations among estimated hourly personal $PM_{2.5}$ exposures, microenvironment exposures, and ambient $PM_{2.5}$ concentrations in *S2*.

In-Residence						
In-Other	**-0.65**					
Outdoor	**-0.24**	**0.09**				
Near-Road	**-0.07**	-0.0001	**0.03**			
Vehicle	**-0.29**	**0.28**	**0.31**	**0.07**		
Ambient $PM_{2.5}$	**0.46**	**0.05**	**0.003**	**-0.001**	**0.02**	
Personal Exposures	**0.49**	**0.06**	**0.10**	**0.03**	**0.12**	**0.84**
	In-Residence	In-Other	Outdoor	Near-Road	Vehicle	Ambient $PM_{2.5}$

Values in bold font represent significant p-values at $p<0.05$ level.