FROM MEASURES TO MODELS: PREDICTING EXPOSURE TO AIR POLLUTION AMONG PREGNANT WOMEN

by

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Abstract

Introduction: Exposure assessment is a key challenge in environmental epidemiology. When modeling exposures for populations, one should consider (1) the applicability of the exposure model to the health effect of interest (i.e. chronic, acute), (2) the applicability of the model to the population of interest, (3) the extent to which modeled exposures account for individual factors and (4) the sources of variability within the model. Epidemiological studies of traffic-related air pollution and birth outcomes have used a variety of exposure models to estimate exposures for pregnant women. These models are rarely evaluated, let alone specifically for pregnant women.

Methods: Measured and modeled personal exposures to air pollutants (nitric oxide: NO, nitrogen dioxide: NO_2, filter absorbance and fine particles: $PM_{2.5}$) were obtained for 62 pregnant women from 2005-2006 in Vancouver, Canada. Exposures were measured for 48-hours, 1-3 times over the pregnancy. Mobility was assessed using Global Positioning System monitoring and self-reported activity logs; individual factors (dwelling characteristics, socio-economic factors) were assessed using questionnaires.

Results: Modeled home concentrations using a traffic-based land-use regression model were moderately predictive of personal samples for NO only (Pearson's r=0.49). Models for NO including home and work locations explained more between subject variance than using home only (4% home only, 20% with home and work). Modeled exposures using ambient monitoring stations were predictive of personal samples for NO (Pearson's r=0.54), absorbance (r=0.29) and $PM_{2.5}$ (r=0.12) mainly due to temporal correlations (within subject variance: NO=37%, absorbance=11%, $PM_{2.5}$=9%). Home gas stove was an important determinant of personal exposure for all pollutants. There was a significant (1 hour/day/trimester) increase in time spent at home with increased trimester of pregnancy.

Conclusions: In this evaluation, based upon repeated 48-hour exposure measurements, models currently used in air pollution studies were moderately reflective of personal exposures, depending on the specific pollutant and model. Land-use regression shows promise for capturing spatial variability, especially when including mobility (work or school locations) in exposures, whereas monitor-based models are better for capturing temporal variability. Future models should include mobility, where possible, and consider the implications of increasing time at home over pregnancy in assessing exposures for pregnant women.

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List of Symbols and Abbreviations

ABS	Absorbance
BAQS	Border Air Quality Study
BC	British Columbia
GB	Georgia Basin
GIS	Geographic Information System
GPS	Global Positioning System
GVRD	Greater Vancouver Regional District
IDW	Inverse distance weighting
LUR	Land-use regression
NO	Nitric Oxide
NO_2	Nitrogen Dioxide
NO_X	Nitrogen Oxides
PAH	Polycyclic Aromatic Hydrocarbons
PHAIR	Pregnancy, Health and AIR pollution study
PM	Particulate Matter
VOC	Volatile Organic Compounds
WA	Washington

Co-authorship Statement

This statement is to acknowledge my role and that of my co-authors in the research presented here.

The land-use regression surfaces used in this dissertation were developed previously by my co-author and supervisor (Michael Brauer) and others (Sarah Henderson). I received SAS code from Lillian Tamburic as a starting point for the ambient monitoring (interpolation) exposure assessment for my study. Sara Leckie and Katherine Rempel helped with the sampling study and analysis of the samples (lab work).

My role in the research was the following: I was primarily responsible for most aspects of the air pollution sampling study: including developing the questionnaires and sampling protocols, analyzing the data and quality assurance. Others, including my co-authors, were involved in the field work including recruitment, collecting data and sample measurement/analysis. I conducted all the geographic information systems work independently, including geo-coding, mapping and GPS route processing. I conducted all data analysis for Chapters 2-4 and prepared the manuscripts, tables and figures. My supervisory committee and co-authors (Michael Brauer, Kay Teschke and Patti Janssen) provided feedback on the manuscripts which has been incorporated in the final drafts presented here.

Chapter 1 Introduction & Literature

Every day, urban residents are exposed to air pollution from motor vehicles and there is increasing concern about the impact of such air pollution on public health. Higher concentrations of air pollutants have been measured in neighbourhoods (e.g. schools and residences) near busy roads (1,2) and have been linked with traffic density or vehicle counts. A growing number of studies have demonstrated associations between proximity to high-volume motor vehicle traffic and effects on human health (3). The increasing evidence of health effects (from traffic pollution) has also led to regulatory actions and policy recommendations (4) (also see Appendix F). Some of the health effects which have been linked with exposure to traffic air pollution include: increased respiratory symptoms (5), mortality from cardiovascular disease (6) (particularly in the elderly and children) and adverse birth outcomes (7).

Birth outcomes which have been associated with air pollution are: low birth weight, preterm birth, and intrauterine growth retardation (8,9), defined as lower than the 10th percentile of birth weight for a given gestational age. The exposure measures most strongly associated in many studies were proximity to traffic (10), the measures of traffic-related pollutants, $PM_{2.5}$, NO_x (including both NO and NO_2) and elemental carbon. Others have investigated the biological mechanisms behind these associations by measuring biomarkers of exposure (DNA adduct levels) to air pollutants (11,12) and demonstrated higher biomarker levels in maternal blood and placentas from women and babies living in areas with elevated pollution levels. A recent review by the Sram et al. described the impact on these biomarkers related to air pollution exposure as "similar to, but smaller in magnitude than, differences between smoking and non-smoking mothers. All this indicates that ambient air pollution levels do translate to higher individual exposures, even for unborn babies."(13)

A large, Health Canada funded cohort study, the Border Air Quality Study[1] (BAQS), is underway in BC and Washington State to examine the impact of air pollution on various health outcomes in this region. One aspect of the study is the investigation of the association between air pollution and adverse birth outcomes for 120,000 births in the BC portion of the Georgia Basin airshed from 1999-2002 (14).

[1] For more information about the Border Air Quality Study, see www.cher.ubc.ca/baqs.

For this birth cohort, air pollution exposure has been estimated using *ambient monitoring station-based methods* and a traffic-based *land-use regression model* (15) that predicts air pollution concentrations at each mother's home address. *Ambient monitoring-based methods* are frequently used in air pollution studies. In these methods, stationary fixed-site air pollution monitoring stations (often called "ambient monitors" or "central monitors") are used to estimate an individual's exposure. If more than one ambient monitor is available (i.e. in the case of regulatory networks with multiple monitoring locations), measurements from multiple sites may be used to generate an individual's exposure estimate. The *land-use regression approach* combines proximity to major roadways or traffic levels and other land use variables (in the context of a Geographic Information Systems) with ambient air pollution measurements in a regression model to establish air concentrations across the area of interest. It is important to note that land-use regression models are relatively novel, are designed to estimate chronic exposures and focus on spatial variability. Although air pollution model evaluation (or validation) studies have been carried out for some subpopulations, to date, no studies have evaluated land-use regression models against personal samples. Additionally, only a few studies have carried out personal exposure monitoring to assess the actual exposures of pregnant women to air pollutants (16,17).

This thesis touches on three themes: (1) the evaluation of exposure methods/models used for population studies of air pollution by comparing to measurements from a personal monitoring study (2) the ability of exposure models to account for individual factors that impact exposure and (3) the air pollution exposure and activities of pregnant women. The following sections of this introduction discuss the current literature related to these themes, describe the models and methods that were evaluated and discuss some relatively novel exposure assessment tools that were used as part of this study. A final section describes the current literature on air pollution and birth outcomes.

Air pollution exposure assessment: Methods and Models

Research studies investigating air pollution and adverse birth outcomes (8) (e.g. low birth weight, preterm birth, intrauterine growth retardation) have used different methods to assess exposure, ranging from exposure surrogates (e.g. city or proximity to traffic) to personal measurements. Nieuwenhuijsen (18) described a hierarchy of exposure data from "worst" to "best" as compared to actual exposure. While "quantified personal measurements" are described as the "best" exposure data available, they are often impractical for large-scale cohort studies. Instead, most studies have used available air pollution monitoring data, exposure surrogates or more complex modeling approaches. In many cases, there is little or no validation of these methods as compared to personal measurements.

Air pollution exposure varies by time and space. Meteorology (local, regional and global trends) and topography play key roles in creating both spatial and temporal variation in ambient air pollution. Similarly, local sources such as traffic and industrial sources have a strong influence, primarily at the spatial level. A third source of variability in population-level exposures is due to mobility, activities of individuals (including exposure to indoor sources) and building characteristics (i.e. infiltration) which will be discussed in the second section of this literature review.

Most commonly, air pollution epidemiological studies and their exposure assessment methods have focussed on either spatial or temporal variability. Beyond simple ecologic comparisons, most air pollution and health studies have used the *temporal* fluctuations in pollution to generate variability in exposure (e.g. time series studies) (19). However, more attention is being paid to the impact that small-scale *spatial* variability can have on exposure. In a review on spatial heterogeneity of air pollution, the authors noted that there are "considerable small-scale variations within urban areas", especially for Ozone and NO_2 (20). To better account for these small-scale area variations, intraurban exposure models (21) are being used more frequently to assess exposures.

Four classes of models (as defined by Jerrett et al. (21)) will be discussed here: proximity approaches, interpolation models, land-use regression models, and "hybrid" models. These models have been used to varying degrees in studies of air pollution and health effects. Where possible, studies of air pollution and birth outcomes, specifically, that use these models are discussed. Some models incorporate only temporal or spatial variability while some consider both.

Proximity Approaches: Surrogates, Buffers or Ambient Monitoring stations

Exposure to air pollution can be defined by a subject's home being in a certain neighbourhood or city. These regional areas are sometimes defined by surrogates that are related to the a priori hypothesis. For example, a study in Taiwan (22) used a traffic-based exposure surrogate of "residence within 500 m of a freeway" and "residences not within that area". This approach defined "buffers" or areas within this distance from a freeway (see Figure 1.1) and assigns a binary exposure (yes=within 500 m, no=outside buffer). This is a typical ecologic approach using buffers. Alternately circular areas or buffers around an air pollution source (i.e. industrial plant) have been used for defining exposed individuals.

A retrospective study (23) used "coal consumption" as a surrogate for air pollution exposure in an ecologic analysis of birth weight in Britain in the 1940's. In a simple example of this type of exposure assessment (), study subjects within the defined "exposed" area could be assigned a "1" and subjects outside the area would be assigned a "0". This method is useful for exploratory analysis; but is subject to significant limitations that contribute to misclassification of exposure and could bias risk estimates. Some limitations include: use of covariates that may confound the relationship between air pollution and health; little consideration of topógraphy, meteorology or emissions types; assumption of exposure at one location (often home or school) as representing all exposure.

The vast majority of birth outcomes studies have assessed exposure using data from the nearest ambient monitoring station (24). Ambient monitoring networks are often maintained by government or regulatory organizations and measure various pollutants. Some cities have multiple monitors, while others have one, or none. Studies using ambient monitors to assess exposure improve on simple ecologic or surrogate approaches by using actual measurement data that provides relative levels of exposure for different areas and times. Two studies, in Brazil (25) and in the Czech Republic (26), both used one monitoring station for all residents within a city. This approach means that the variability in exposure is only from temporal differences in air pollution at one site. Specifically, for birth outcomes studies, the only variability in exposure is due to differing birth dates/pregnancy periods. In this example, if two women were pregnant for the same period and resided within the same city, this approach would assign them identical exposures.

However, monitoring stations are appropriate for exposure assessment in time-series studies where the exposure window of interest is acute (days). Time series studies use the daily fluctuations in air pollution in combination with daily health outcome data to investigate relationships between these two. Using true time-series methods when studying birth outcomes is problematic because the hypothesized biological mechanisms (of air pollution's impact on the fetus) suggest more chronic (e.g. month or trimester-long) exposures are of concern (7). However, if there was a pre-existing hypothesis that a specific health effect (e.g. birth outcome) was due to an exposure during a specific, short-term window, then time-series methods could be appropriate.

Some studies have incorporated more than one monitoring station to add a spatial component to their exposure assessment. Some have averaged exposure over days, months or years using the mean measurements taken by the air quality monitoring station *nearest* to the mother's residence.

With the "nearest monitoring station" approach, all subjects within range are assigned exposures from that station regardless of how far they live from the monitoring station; these approaches are clearly influenced by the density of the monitoring station network and the ability of the monitoring stations to capture neighbourhood-level variations. Again, if two women resided in the same area near a monitoring station and were pregnant at the same time, they would be assigned identical exposures. In general, most studies rely heavily on ambient monitoring data (27-31).

Figure 1.2 shows an example using a "nearest station" approach for Vancouver and displays the monitoring stations used. The areas with different colour shading represent the areas that are defined by one monitoring station. In this case, with a fairly dense monitoring station network, a moderate amount of spatial variability is observed. A nearest monitoring station approach was evaluated as part of this thesis.

Interpolation Methods

Interpolation models improve over proximity models by using geostatistical techniques to estimate concentrations between known data at known locations. These "known" data can be either traffic volumes on streets or ambient monitoring stations. A birth outcomes study in San Francisco (10), calculated an inverse-distance weighted traffic density metric (using road type and traffic volume) to represent proximity to traffic for each residence. Another study (32) compared exposure metrics (calculated using nearest monitor, average of all monitors and inverse-distance weighted average of all monitors - all within a 5-mile radius) in a study of $PM_{2.5}$ and birth outcomes in California. These authors found little differences (very high correlations) between inverse-distance weighted, average and nearest monitor methods within a 5-mile radius.

This study evaluated an interpolation approach using the inverse distance weighted (IDW) average of the nearest 3 monitoring stations data to an individual's home (see Appendix A for details about IDW). A visual representation of this approach is shown in the right panel of Figure 1.2.

Land-Use Regression Models

Land-use regression models are based on combinations of measurement data, land-use and traffic variables and are generated using Geographic Information Systems (GIS). The general approach used to generate a land-use regression model (also called a "surface") is as follows. Ambient pollution data is collected via a sampling campaign in the area of interest. Sampling sites may be selected randomly or using mathematical algorithms that target the variability in concentrations and in other variables of interest (e.g. population). Geographic predictor variables are then generated using geographic characteristics at the sampling sites (i.e. population, road lengths, road density, elevation, land-use categories or traffic density). A regression approach is then used to identify geographic variables that are predictors of the sampling/measurement results at those sites. Predictor variables for the whole study area (not only at the sampling sites), and are then used (with the intercepts and coefficients from the regression at the sampling sites) to generate predictive pollution "surfaces" for the whole stúdy region.

In general, a land-use regression model can be used to predict individual-level exposure at any location based on surrounding land use and traffic patterns. This approach can be adapted for other urban or geographic regions; however the individual models are area-specific. It is thought that these land-use regression models can improve exposure assessment by accounting for a finer level of spatial variability of exposure for some pollutants.

At this time, air pollution exposure assessment using land-use regression models has been applied to relatively few studies. Two models were developed for European cities (33,34) and have been used to investigate adverse effects of air pollution on health outcomes *other* than birth outcomes (35-38). A recent study used a land-use regression model for a marker of diesel exhaust to investigate relationships with infant wheeze (39). Other land-use regression models have been developed (San Diego & Los Angeles, USA; Toronto & Hamilton, Ontario) (40-44) and there are ongoing health effects studies using these models (most not yet published). This thesis evaluated exposures based on a land-use regression model that was developed for the Greater Vancouver Regional District (15) and has been used for a study of birth outcomes and air pollution (14).

Exposure Evaluation

A critical component in the development of any air pollutant exposure estimate is that it should be evaluated in comparison to personal exposure measurements (21,45). The simplest way to use a model to predict personal exposure assumes that the exposure of the individual is dominated by their exposure at their home location. In the case of many population-based epidemiological studies, only home address (or postal code) is available. However, personal exposure is often poorly correlated with ambient monitoring data (27-31) and land-use regression models are designed to predict ambient concentrations. This thesis is the first to evaluate land-use regression models in comparison with personal exposure measurements.

A few studies have attempted to evaluate the use of "living near a busy road" (46) or traffic density and urbanization (47) as indicators of personal exposure in children and have demonstrated contrasts in personal exposure using these metrics. However, these studies were all conducted in Europe and may not be transferable to areas with lower road and population densities. In one study, self-reported traffic intensity was compared to land-use regression estimates of traffic volume (48) but no published studies have evaluated land-use regression based estimates of air pollutants with personal measurements. A comparison of measured and modeled volatile organic carbon (VOC) exposures was conducted in Baltimore, Maryland. The model assessed was the US Environmental Protection Agency's Assessment System for Population Exposure Nationwide (ASPEN) and the investigators assessed differences between measured and modeled exposures using the ratio between the two. Ratios for Benzene and Carbon Tetrachloride were relatively close to 1 whereas ratios for most other VOCs were much greater than one (poor agreement). In this case, the model was, according to the authors, "reasonably accurate as a surrogate for personal exposures ... for VOCs emitted primarily from mobile sources or VOCs that occur as global "background" source pollutant with no indoor source contributions" (49). Overall, relatively few model evaluation studies have been conducted to date and none have specifically evaluated land-use regression based estimates.

Improving on Land-Use Regression: Hybrid Models

Personal monitoring can be combined with other modeling approaches to create so-called "hybrid models" (21). Liu et al. used a combination of outdoor ambient stations and personal monitoring (50) to predict personal exposure. Similarly, others (28,51) measured both personal, school and fixed-site concentrations and evaluated the impact of these different exposure assessment methods on the health outcome associations. Dispersion models (52) or traffic-density (interpolation techniques) (53) have also been combined with daily diary or time-activity data. In a more complex application, a recent study used GIS to model air pollutant exposure during "journey-time", i.e. time spent in traffic or travel, to enhance personal exposure models to air pollutants(54,55). These "hybrid" modeling approaches have been used primarily in cohort studies among children or older men; never for pregnant women. No studies prior to the study described in this thesis have attempted to combine land-use regression models with personal activity or mobility data to improve estimated personal exposures.

This thesis evaluated both land-use regression and ambient monitoring modeling approaches by comparing modeled estimates to personal measurements.

Error in air pollution modeling

In general, exposure models used for population-based air pollution studies can be subject to both Berkson and classical error (56). Classical error occurs when a measurement varies around some true value and is generally thought of as the error due to a measuring device. Since most exposure models are based on some measured value there is usually a component of classical error due to the measurements. Berkson error occurs when an average value is assigned to individuals within a group. When personal measurements are used to assess individual exposures there is usually only classical error. Since most air pollution studies assign exposures using grouped (spatially or temporally) exposures, most also have some Berkson-type error.

When grouping exposures in air pollution studies, groups could be defined by individuals having similar postal codes, living in the same census tract or living in the same neighbourhood. A simplified list of possible error structures and their causes when individuals are grouped (e.g. by postal code or census tract) are shown in Table 1.1. However, the actual error structure when using fixed-site ambient estimates (in time-series analysis) is quite complex (57). As described by Heid et al. (58), the impact of these different types of error on effect estimates in health studies differs among error structures. In general, classical error can attenuate dose-response slopes whereas Berkson error will either magnify or have no effect (56,58).

Impacts of individual factors (e.g. Mobility) on air pollution exposure assessment

Once an air pollution exposure model or approach has been defined, we must define the relationship between an individual study subject and their predicted exposure. Most commonly, an individual's home residence (address or postal code) is used to define their exposure for the duration of the study period. In other words, we assume that exposure is well-characterized by exposure at home. This excludes the impact of mobility (i.e. where they work, commuting) or other activities on their exposure. On the other hand, activity studies have shown that most people spend a significant portion of their time at home (mean 60-85%) which supports the use of home exposure as a surrogate for total personal exposure (59). Also, in many cases (e.g. cohorts defined using administrative data) only home address is available for exposure assessment in epidemiological studies.

Geographic Information Systems can be used to precisely locate a person's home in space. This is often called geo-locating or geo-coding. For models lacking a spatial approach, there is no need to geo-locate a person's residence to obtain an exposure estimate; however, most models do have some spatial component. Other tools such as the Global Positioning System (GPS) and time-activity logs can be used to incorporate mobility in exposure assessment.

Geographic Information Systems (GIS)

Recently, there has been an increased use of geographic information systems (GIS) for air pollution exposure assessment (60-62). This tool may be used in different ways: from simply locating addresses relative to a known monitoring station, road segment or central site, to more complex land-use regression modeling (21). A recent summary article described the roles of GIS in the various exposure estimation methods (54) and described three applications of GIS: locational, interpolation and dynamic modeling. The first (locational) includes locating points, buffering and distance calculations and is very widely used in air pollution exposure assessment. The second includes kriging[1], inverse-distance weighting and land-use regression mapping. Due to the availability of GIS tools that automate kriging and inverse-distance weighting and assist with regression modeling, these techniques are becoming more common.

There are several examples of locational uses of GIS in air pollution studies. A study in San Diego, California used GIS to calculate traffic densities in a buffer around children's homes for use in exposure assessment (63). Similarly, a birth outcomes study in Los Angeles used GIS to geolocate homes and then calculated a distance weighted traffic density metric in a buffer around each home(10). A study in Sweden (64) estimated historical exposure to ambient air pollution for a study of lung cancer using GIS by geolocating subjects' addresses (over 50 years) and using dispersion modeling. Another study used GIS (65) to calculate distances from subjects' homes to major roads to generate a traffic-based indicator of exposure (using land-use regression). This study used *both* traffic and regional exposure models to account for contributions of local (traffic) and regional background

[1] Kriging is a geostatistical technique used to interpolate (using a linear least-squares estimation algorithm) between values using values at nearby locations.

in their exposure assessment. Another recent example used GIS to geolocate residences and developed an "exposure opportunity score" for exposure to petrochemicals in Taiwan (66).

Understanding Mobility

As noted by Jerrett(21), "while researchers have expended considerable effort on characterising the spatial and temporal distributions ... much work remains in understanding the role of individual mobility..." Because of intraurban variability in pollutant concentrations, individual mobility or "where people go", can significantly impact personal exposure. For any large cohort study, the contribution of both individual mobility and activities (i.e. exposure to environmental tobacco smoke or gas cooking) will likely influence the ability of the air pollution models to estimate exposure.

Two key questions related to this are: (1) How much does individual mobility and/or personal activities influence exposure and conversely, can we still estimate exposure accurately (precisely) without individual knowledge regarding these factors –i.e. for populations? (2) If these factors are important, then how much detail do we need at the individual level to improve exposure models? One of the goals of this thesis was to address (in part) the first of these questions.

There are many ways to capture information about personal mobility that may influence population exposure models. Time-activity (mobility) data are often collected for health outcome studies for a "determinants of exposure" analysis to uncover activity-related predictors of specific exposures. Recent work in Europe has modelled air pollutant exposures in various micro-environments in combination with activity and mobility data to develop integrated exposure models (55).

Global Positioning System (GPS) tracking is in wide use for civilian and military applications. Researchers have slowly begun to use GPS tools for environmental epidemiology applications; however, few studies exist at this time. In one case, personal mobility data (captured using GPS tracking) was used to estimate pesticide exposure in children (67). Researchers in the Oklahoma Urban Air Toxics Study attempted to validate 24-hour activity diaries (68) using GPS tracking data but collected insufficient data due to equipment failures. Nevertheless, the authors concluded that the technology showed promise for future research applications. A recent study (69) compared a mobility data measured by a GPS unit worn by a child and the parents' completion of a standard time-activity diary (log) during the same weekend day and observed relatively low concordance between the methods (kappa =0.33-0.35). No other studies have collected *both* time-activity and mobility data for use in specifically in air pollution exposure modeling approaches. This thesis describes the application of individual-level (personal activity factors) and mobility data as modifiers of modeled exposures.

Activity Patterns of Pregnant Women

Activity pattern surveys have been conducted in the US and Canada. Two large scale studies used almost identical methods in the US (National Human Activity Patterns Survey, NHAPS) and Canada (Canadian Human Activity Patterns Survey, CHAPS) and were designed to provide data for use in exposure assessment modeling (59,70,71). These two surveys collected information using 24-hour time-activity diaries from participants (selected randomly in targeted cities) using Computer Aided Telephone Interviewing (CATI) surveys. Respondents logged the time they spent in all micro-environments during a 24-hour period and then asked specific questions related to exposures in these microenvironments. The focus of the CHAPS and NHAPS surveys was on exposure to water and air-based contaminants.

This data can be used in various ways. For example, assuming people spend time in different micro-environments (e.g. home, school, transit, work), models can be developed that sample from the distribution of activity pattern survey data and combine that with measurement data to predict population mean exposure and *variability*. These models can be used in age-group specific analysis to estimate percentages of the population that may be highly exposed. A recent model was developed to predict particulate matter exposure ($PM_{2.5}$) for 11 age-gender population subgroups in Toronto, Canada using CHAPS data (72). Similarly a study in 2005 (73) used NHAPS data to determine the probability and distributions of exposures in the U.S. population to contaminants that enter the home via the water supply.

Information on the activities and mobility patterns of women during pregnancy is sparse in the literature. Neither NHAPS nor the Exposure Factors Handbook (US-EPA) contains specific information for women during pregnancy. The Canadian Human Activity Pattern Survey (CHAPS) did evaluate pregnancy status of subjects, but only 22 of the 2301 respondents to the survey were pregnant (71). Activities of women during pregnancy have been discussed extensively in the research, but these studies have focused on physical exercise levels (74,75) and body image/physical weight relative to activity patterns (76). A recent review of studies on physical activity during pregnancy and their relationship to physiological health reported that a key limitation in their review of the issue was the lack of well-conducted longitudinal investigations of activity patterns among pregnant women related to physical activity during pregnancy(77). No studies have specifically considered changes in location-activity patterns or microenvironments over the course of pregnancy. This thesis collected activity data specific to women during pregnancy, compared these data to non-pregnant women and evaluated changes in activity over pregnancy.

Air Pollution and Birth Outcomes

One of the primary aims of this thesis was to evaluate the modelled estimates which will be used in a large cohort study (BAQS). The BAQS study tests for an association between modelled air pollutant exposures of the mothers and adverse birth outcomes for their infants (14). Because this thesis relates directly to the cohort study, the current literature on the association between air pollution and birth outcomes will be discussed in brief.

A chapter in a 2005 report published by the World Health Organization (Effects of Air Pollution on Children's Health and Development) (13) reviewed the evidence that exposure to ambient air pollution is associated with a range of pregnancy outcomes. The same authors also published a review article (7) that examined over 50 journal articles (up to 2004) where linkages between ambient air pollutants (including: Polycyclic Aromatic Hydrocarbons (PAH), Sulphur Dioxide (SO_2), Total suspended particles (TSP), Ozone (O_3), PM_{10}, $PM_{2.5}$, NO_2 and NO_X and Carbon Monoxide (CO)) and Intrauterine Growth Retardation (IUGR), preterm birth, birth weight, childhood mortality, and/or birth defects were studied. A summary of the conclusions from this review are presented in Table 1.2.

A 2005 review (24) reported an estimated 5% increase in post-neonatal (28-364 days) mortality and 22% for post-neonatal mortality linked to respiratory disease for every 10 $\mu g/m^3$ increase in particulate matter (PM_{10}). A 10 ug/m^3 increase in particulate matter concentrations is used to facilitate comparisons across studies. The authors did not use a formal meta-analysis because of a lack of studies with similar outcome, criteria and design. Instead, they separately considered results from 5 studies that examined similar outcomes (post-neonatal mortality) using various study designs (ecologic, time-series, retrospective cohort and population-based case-control).

A brief overview of the magnitude of the impacts reported in some studies is shown in Table 1.3. These results suggest that birth outcomes may be especially sensitive to toxic effects of air pollution. A range of study designs were used. The most common study design (13 studies) was a cohort design (usually defined by administrative data) where mean pollutant measurements for a city or district were averaged over pregnancy or the infant's life. Other study designs included time-series (3 studies), prospective cohorts (2 studies) with exposure measurements and case-control studies (3 studies).

The main limitation of previous studies on air pollution and birth outcomes is the lack of consistent and individual-level exposure assessment data. Recent studies have shown that improved assessment of within-city variability in exposure had a significant effect on the magnitude of the risk (of death and cardiovascular events) from increased ambient air pollution (78,79). This suggests that improving exposure assessment models (for pregnant women) to account for within-city variability could have an impact on birth outcomes studies as well.

Most studies of air pollution and birth outcomes assessed exposure using geographic comparisons or nearest ambient monitoring station approaches. A few studies have considered within-city exposure variability using distance-weighting or dispersion modeling techniques. For example, a nested case-control study in the Los Angeles basin (10)used a distance-weighted traffic density (DWTD) measure to calculate risks of being low birth weight or preterm birth per quintile of DWTD. In this study, a relative risk (RR) of 1.08 (95% C.I. 1.01-1.15) for preterm birth was reported for infants in the highest quintile of exposure to traffic. No birth outcomes studies have used land-use regression models to assess exposure.

Only two studies (17,80) have conducted personal air monitoring specifically for pregnant women. One study measured personal exposures to polycyclic aromatic hydrocarbons (PAHs) with 48-hour air monitoring during the third trimester for 348 pregnant minority (African-American and Dominican only) women living in New York City. For African-American women in this study, PAH was positively associated with a decrease in birth weight after controlling for confounders[1]. A second study (17) measured 48-hour personal exposures to $PM_{2.5}$ for 407 non-smoking pregnant women in Krakow, Poland during their 2nd trimester. Exposure to $PM_{2.5}$ in this study was associated ($p=0.03$) with a decrease in birth weight after controlling for confounders[2].

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[1] BMI, parity, cotinine, sex of baby, and gestational age

[2] Size of mother (maternal height, pre-pregnancy weight), parity, sex of child, gestational age, season of birth, and self-reported environmental tobacco smoke

Research Objectives

The overall objective of this thesis was to measure personal exposure to air pollutants among a sample of pregnant women and to use these empirical measurements to evaluate two exposure estimation methods. Other factors that could affect agreement between model estimates and measured exposures were also investigated: specifically, the impacts of individual mobility, building characteristics, demographics and activity patterns. A third objective of this work was to characterize activities of pregnant women and changes in activity over the period of pregnancy.

Research Questions

The specific research questions addressed in this thesis are as follows. Chapters which primarily address each question are noted.

1. Are differences in personal exposures of individual pregnant women to air pollutants predicted using population-level exposure modeling methods, specifically land-use regression and ambient monitor data? (**Chapter 2**)
2. What are the impacts of mobility on Question 1? (**Chapter 2**)
3. What are key sources of personal-level variability in the personal exposures of pregnant women to the measured pollutants? (**Chapter 3**)
4. Are activities of women during pregnancy different from women in the general population? (**Chapter 4**)
5. Do individual mobility and activities of women change during pregnancy (across trimesters) and by season? (**Chapter 4**)

Chapter 2 of this thesis describes the sampling study and the exposure models which were evaluated: land-use regression and two approaches using ambient monitoring data. This chapter goes on to evaluate the air pollution exposure assessment models by comparing the personal measurements to modeled estimates at the home residence of the mother. This chapter also presents the impacts of individual mobility (using work location) on modeled exposure. The relative ability of the exposure models to represent spatial and temporal variability in personal exposures is also discussed. These exposure measurements and models were further used in Chapter 3.

In **Chapter 3**, sources of individual variability in personal exposures to air pollution were identified by developing empirical models to predict exposure to air pollutants for pregnant women. Individual factors considered in this analysis were: socio-economic data, time-activity information, dwelling (home and work) characteristics, and the modeled exposure estimates from Chapter 2.

Lastly, in **Chapter 4**, the activity and mobility data from this study population (pregnant women) was compared to a population sample of non-pregnant women. The activity patterns were also examined for any changes in activities across the period of pregnancy.

A final chapter in the thesis (**Chapter 5**) describes the key findings of this work, strengths and limitations and implications for future studies.

A significant part of this thesis was the personal monitoring study of pregnant women in Vancouver, Canada. An appendix is attached (**Appendix A**) with detailed methods for the sampling study. This appendix also describes how exposures were modeled for this population using the GIS and GPS tools (including the specific software tools and methods). **Appendix B** contains the study questionnaires, consent form, sampling data collection sheets and ethics approval. **Appendix C** describes a simulation (using a Monte Carlo model) to estimate the influence of additional (not home or work) mobility on modeled exposures. **Appendix D** presents the calculation of a particulate matter distribution cutpoint when running an impaction sampler with an altered flow rate as used in the sampling study presented in this thesis. **Appendix E** contains detailed results tables including descriptive results tables not presented in the chapters. **Appendix F** contains policy guidelines (specific to air quality issues around site development and urban planning) that were prepared for a BC Ministry of Environment document on urban and rural land development (4) (extracts are shown) and supporting documentation that was prepared for the Ministry related to these policy guidelines. The supporting documentation contains a discussion of the legislation related to setbacks, a review of studies that measured traffic pollutants at distances from major roadways and sources of information about traffic intensities in BC.

Figures and Tables

Figure 1.1 Examples of 2 buffering methods: Distance from freeway (left) and circular buffer around point source (right)

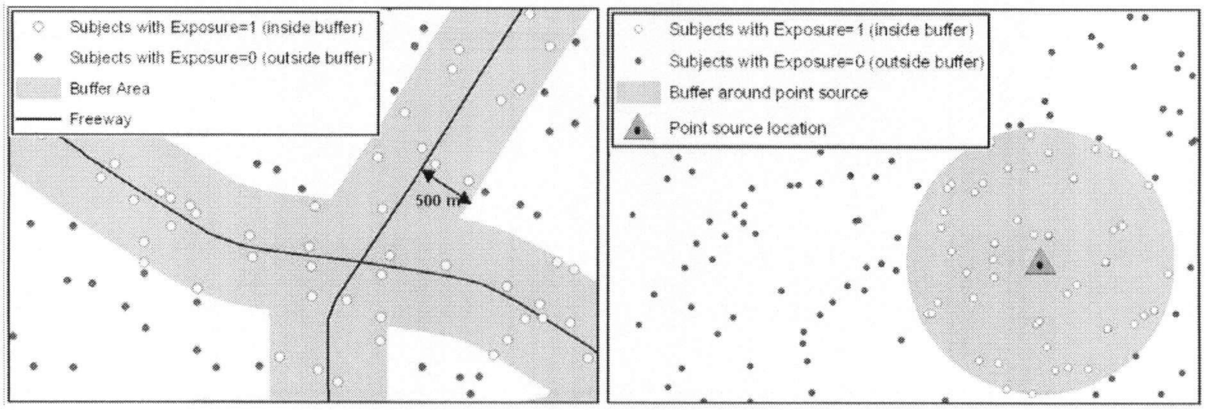

Figure 1.2 Example of Nearest Monitoring Station and Interpolation using Inverse Distance Weighting for Vancouver, Canada

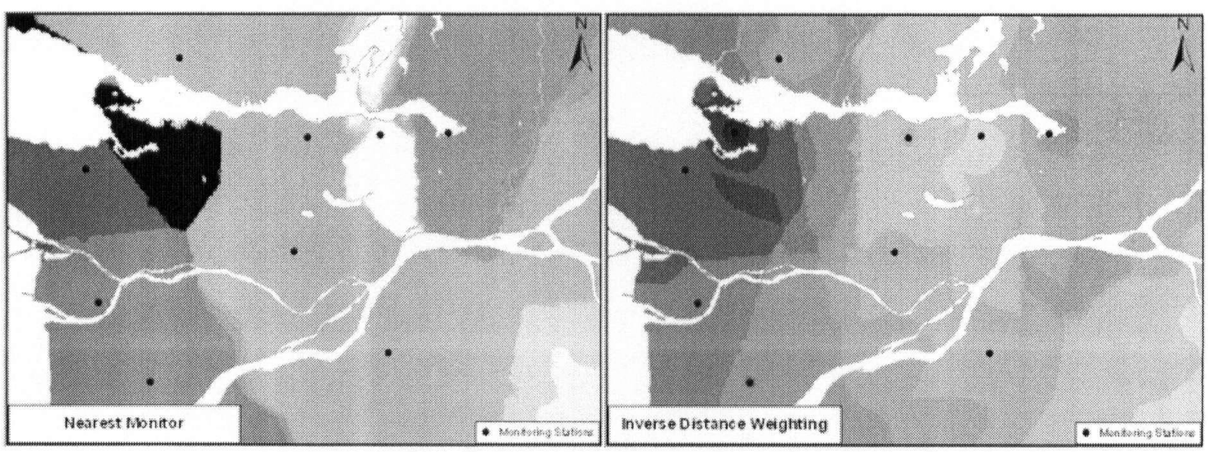

Figure 1.3 Land Use Regression Surfaces for Vancouver, Canada

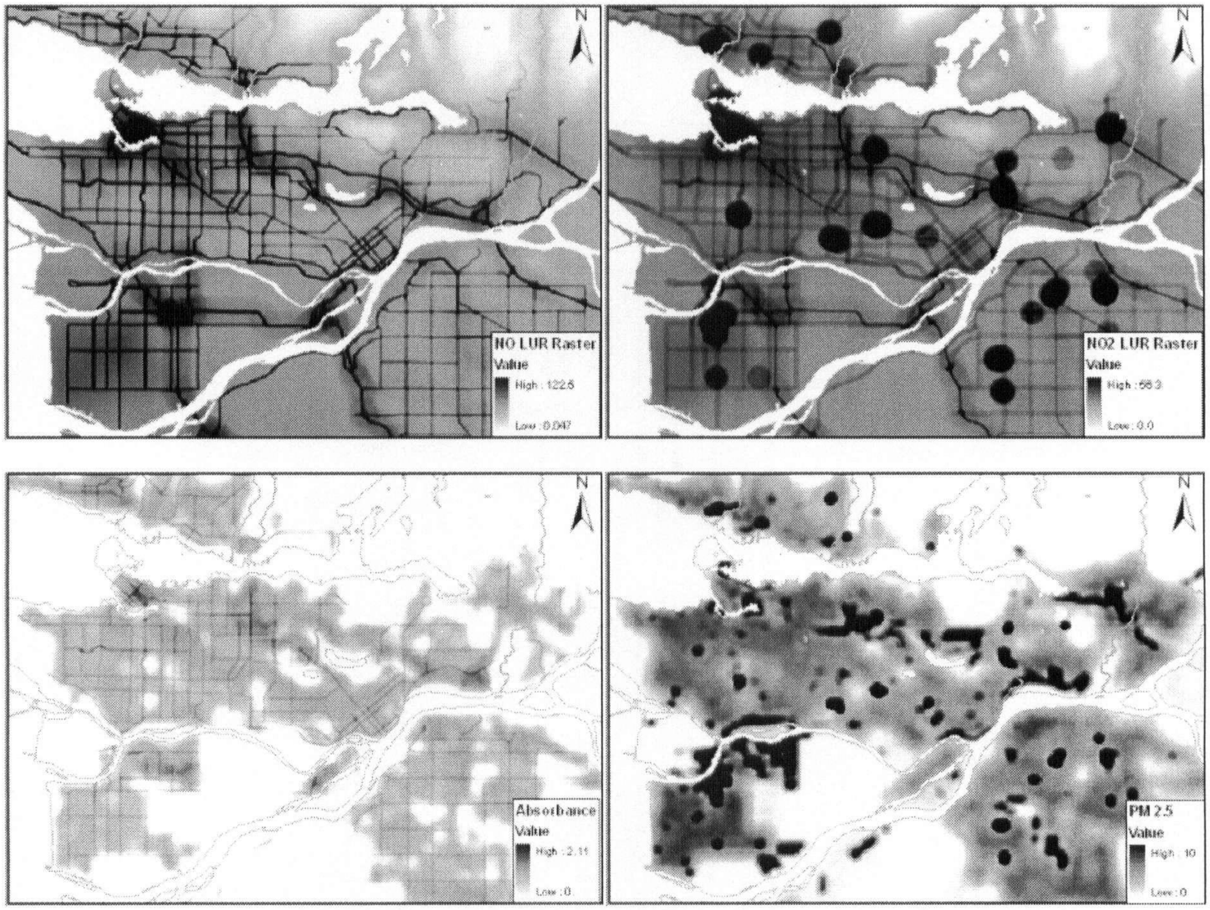

Table 1.1 Descriptions of error structures in air pollution exposure models when individuals are grouped (e.g. using postal code, census tract)

Exposure Models	Error type	Description
1. Distance to roads	Classical	Error in group measurement of distance to road
	Berkson	Error from using group's distance to road as a proxy for individual's distance to road
2. Ambient fixed-site monitors (nearest) or interpolation	Classical	Error in measurements using fixed-site monitors (lab, device, sampling error, calibration); Error in time-period of exposure
	Berkson	Error from using ambient monitoring measurement as a proxy for individuals' personal exposure
3. Land-use regression	Classical	Error in sampling measurements collected for development of the model; error in geocoding and geographic information system variables; error from temporal trends (if used), model error
	Berkson	Error from using exposure models as a proxy for personal exposure

Table 1.2 Summary of conclusions for evidence of causality for exposure to air pollution and birth outcomes reported by Sram (7)

Health outcome	Evidence
Infant deaths from respiratory causes, during post-neonatal period (28-364 days)	Sufficient evidence for causality
Birth weight (Low birth weight, LBW); defined as < 2500 g	Sufficient to *suggest* causality, need further study
Intrauterine Growth Retardation (IUGR); defined as weight at birth < 10^{th} Percentile for gestational age and sex	Insufficient to infer causality, but demonstrates clear trends, needs further study
Pre-term birth or Pre-term Delivery (PTD); defined as <37 weeks of gestational age	

Table 1.3 Summary of RR/OR results, adapted from (8,9,24)

Health outcome	Exposure[1]	No. of Studies	RR/OR (range)
Post neonatal mortality (respiratory)	PM or TSP	4	1.2-1.26, CI >1.0 for 3/4 studies, for 10 μg/m^3 increase
Post neonatal mortality (all-cause)	PM or TSP	5	1.04-1.12, CI > 1.0 for 4/5 studies, for 10 μg/m^3 increase
Low birth weight	SO_2, CO	7	SO_2: 1.0-1.04, CI >1.0 for 3/5 studies, for 10 μg/m^3 increase CO: 1.18-1.28, CI >1.0 all studies, for 1 mg/m^3 increase
Intrauterine Growth Retardation (IUGR)	$PM_{2.5}$, PM_{10}	4	2/4 studies show positive associations; $PM_{2.5}$ OR 1.2 for 10 μg/m^3 increase in first month, CI >1.0. Or, OR=1.06 for each trimester (time-series study), CI>1.0.
Pre-term birth	Most ecologic or combined pollutants	9	8/9 positive associations, but often very small (OR 1.02-1.1)

[1] These are exposures that appear to show positive associations and consistent trends across studies.

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Chapter 2 Evaluation of Ambient Air Pollution Exposure Assessment using Personal Measurements of Pregnant Women: Implications of Space, Mobility and Time[1]

Introduction

There is a growing body of research demonstrating adverse effects of outdoor air pollution on birth outcomes (1,2) (e.g. low birth weight, preterm birth, intrauterine growth retardation). As with all air pollution studies, studies of birth outcomes have used different methods to assess exposure: nearest monitor (3), interpolation methods (4), or traffic-based metrics (5). Various studies have reported associations between modeled exposure to traffic-related air pollution and adverse birth outcomes (5,6) but these models have not yet been evaluated. A few small cohort studies have measured personal exposure at 1 or 2 time-periods during pregnancy (7,8) but there are very few air pollution measurement studies focusing specifically on pregnant women.

Recent studies have identified the importance of capturing within-city spatial variability in air pollution exposure in addition to temporal variability (9,10). Specifically, studies of traffic exposures have used indicators (i.e. living near a 'busy' road) (11), traffic volume or density measures (5,12) or more complex traffic-based metrics using land-use regression (13) to capture within-city spatial variability. Land-use regression models use a combination of measurement data and traffic/geographic variables to estimate within city variations in traffic-related air pollution (14,15). Generally, traffic-based models (including land-use regression) have little or no temporal variability and are used to assess impacts of chronic exposures. A few studies have attempted to evaluate the use of "living near a busy road" (16) or traffic density and urbanization (17) as indicators of personal exposure in children and have demonstrated contrasts in personal exposure using these metrics. In one study, exposure to self-reported traffic was compared to land-use regression estimates of traffic

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[1] A version of this chapter will be submitted for publication.

volume (18) but no published studies have evaluated land-use regression based estimates of air pollutants against personal measurements.

In evaluating assessment of exposure for large population studies we suggest some key questions to be considered: First, how well do these exposure models estimate personal exposure, secondly, is it possible to improve exposure estimates by incorporating mobility data or other information that may be available for all individuals, and thirdly how well does the exposure estimate characterize spatial vs. temporal variability? For example, although people spend between 60-80% of their time at/near home (19), including subject-level mobility such as time spent at work or in transit could improve exposure assessments (20). Others have suggested that time spent in transit may be responsible for increased exposure due to the increased proximity to traffic during this activity (21). The relative contribution of spatial and temporal variability to an exposure estimate is also important. Depending on the health effect being studied, either high spatial or temporal precision may be more important for detecting an association. Very few studies have evaluated air pollution estimation methods commonly used in a large cohort study in comparison with personal sampling. Using personal monitoring, we collected short-term personal air pollutant measurements for a sample of pregnant women and compared these to their modeled concentrations using fixed-site monitoring and land-use regression. By collecting repeated measures per subject, we could examine the ability of the models to capture spatial and temporal variability for the subjects.

Methods

Study subjects

We recruited a sample of 62 pregnant women living in the Vancouver metropolitan area in 2005-2006. Subjects were limited to healthy, low-risk pregnancies and non-smokers living with non-smokers and were recruited through prenatal classes (yoga, educational), word-of-mouth and other posters/outreach. The study protocol and material was approved by the University of British Columbia Behavioural Research Ethics Board (approval #B05-0441).

Exposure measurement and estimation

For each study subject we generated exposure estimates to NO, NO_2, $PM_{2.5}$, and filter absorbance[1], using three approaches: personal sampling, using ambient monitoring data linked to home locations, and using concentrations from land use regression models developed previously (22).

Personal exposure measurements and activity recording

Each woman carried personal air monitoring equipment and a Geographic Positioning System (GPS) datalogger in a small backpack or shoulder bag (with the air monitors attached to the shoulder strap of the bag to approximate the subjects breathing zone), and completed a self-administered time-activity diary on one, two or three 48-hour sampling sessions spaced 3 months apart (i.e. in each trimester of her pregnancy). Due to the difficulty of recruiting women in their first trimester, most subjects were in their second trimester when recruited, thus completed only two sampling sessions. We encouraged subjects to wear the sampling equipment while moving about and to place it on a table or chair near their current location when sitting. At night, the women were advised to place the sampler outside the bedroom if the noise was disturbing to them.

We measured personal Particulate Matter ($PM_{2.5}$) with Personal Environment Monitors (PEM, MSP Corp, USA). The PEM was loaded with a pre-weighed 37-mm 2μm-pore size Teflon filter connected to a battery powered sampling pump (SKC Leland Legacy, city) set to a flow rate of 5 L/min. This flow rate, which results in a 50% cutpoint of 2.2 $\mu g/m^3$, was used because of the availability of sampling pumps and collected a sample more representative of traffic-combustion generated fine particles. Triplicate mass measurements were made in a temperature (23 °C, SD=0.77 °C) and humidity-controlled (34%, SD=3%) weighing room as described previously (23). The limit of detection, calculated as three times the standard deviation of the laboratory blanks, was 1 $\mu g/m^3$ based on a 48hr sample.

After weighing, we measured the reflectance of each filter using a Smoke Stain Reflectometer (Diffusion Systems Inc.) according to a standard method and calculated the absorbance (SOP ULTRA/KTL-L-1.0 1998). The limit of detection of absorbance was calculated as 0.1 10^{-5} m^{-1} based on 3 times the standard deviation of the blanks. NO and NO_2 were measured using Ogawa passive

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[1] Filter absorbance is a measure of the "blackness" of a filter used to collect a particulate sample. Previous studies have shown that absorbance measures are highly correlated with elemental carbon concentrations. Details are in Appendix A.

samplers (Ogawa Inc. Pompano Beach, FL). After sampling, filters were placed in de-ionized water and the resulting nitrite concentration was determined by ion chromatography. Limits of detection were 0.45μg for NO and 0.20μg NO_2 mass.

The GPS dataloggers (BlueLogger, DeLorme Inc.) recorded latitude, longitude, time, speed every 5 seconds while a GPS signal was detected. We added a battery pack (Alti-tech Inc.) to extend the continuous run-time to at least 48 hours. Prior to each sampling session, we confirmed that a GPS signal had been acquired near the location of the start of the session. GPS devices commonly lose their satellite signal when inside buildings and can take some time to obtain a new fix after exiting a building. To avoid overburdening the subjects and having them alter their activity patterns, we did not instruct participants to wait outside a building for the GPS to regain its satellite connection. We also wanted to evaluate the technology's application to exposure monitoring studies when participants were specifically instructed to ignore the equipment. The GPS data were downloaded at the end of each sampling session. According to the manufacturer's specifications, the GPS loggers' accuracy is within about 10 m assuming a full signal (3+ satellites) and clear sky-view.

In the activity log, subjects recorded their location as indoors at home/work/other, outdoors, or in transit during each ½ hour period. Up to two locations could be indicated during each ½ hour period. For each activity log, we calculated the percentage of time each subject spent at home, work or in transit. For GPS route data, points within 350 m of home and 400 m of work were identified as "at home" and "at work" respectively, and we calculated similar percentages of time spent at home and at work from these data.

Geo-coding addresses and postal codes

For each subject, we geo-coded the home and work address *and* postal code using ArcGIS/ArcMap (ESRI v9.1, Redlands CA, USA). Addresses were geocoded in ArcGIS using the CanMap Streetfiles, 2001 (DMTI Spatial Inc., Markham, Canada) road network and automated address locator which was successful for about 40% of the addresses; the rest were manually located or adjusted using Google Earth (v3.0, Google Inc., Mountain View CA, USA). In some cases, the subjects' addresses were on roads that were not included in the DMTI road network (new subdivisions). Since geocoding may mis-locate addresses by as much as 100 meters for large building footprints, we obtained land parcel data (lot boundaries and addresses) from the municipalities (2004-2005) in the study area and combined these with attribute data from BC Property Assessment (24). All home and work address points were verified manually and adjusted to the center of the street-facing portion of the land parcel for each address. In some work locations or apartment buildings, parcel data did not exist for the exact address. In these cases, the address was shifted off of the street segment to a location nearest to the lot with the closest address on the same side of the street.

Generally, only postal codes are available in population-based epidemiology studies due to privacy concerns. Therefore, we geocoded both addresses *and* postal codes because we were interested in comparing the exposures estimated using both location parameters. In Canadian urban areas, postal codes can represent an area as small as an apartment building or a block face. All postal code locations (centroids) in Canada were obtained from the CanMap Multiple Enhanced Postals (MEP) (DMTI Spatial Inc., Markham, Canada) and study participants home and work postal codes were extracted from the MEP file.

Exposure estimates using land-use regression models

The land-use regression models generate raster (continuous) surfaces with a resolution of 10x10m covering the whole of the Greater Vancouver Regional District (Figure 2.1. Briefly, the models were based on exposure data generated from a 2003 sampling campaign (112 samples for NO, NO_2; 25 samples for Absorbance and $PM_{2.5}$). Geographic predictors (n=98) representing road density, land use, population, elevation, and traffic density were generated for the 2003 sampling sites and used in regression models to predict measured concentrations. The model coefficients and intercepts were then summed with the predictor surfaces in ArcView (ESRI v 3.0) to generate the surfaces from which estimates of concentration at any location in the study area could be obtained. The surfaces were smoothed using an ArcGIS Spatial Analyst (ESRI v.9.1 2004) tool which decreased the resolution to about 30x30m because of a concern that small errors in geocoding would cause large numeric changes in the exposure estimates.

A unique feature of these models was that they also made use of additional ambient exposure monitoring network data from 1998-2004 to generate adjustment factors for monthly temporal variation. These monthly adjustment factors were applied to the exposure surfaces, making it possible for us to generate land-use regression exposure estimates for this study that corresponded to the same month as the personal samples, for each subject / sampling session combination. Both annual and monthly-adjusted land-use regression surfaces were used for all pollutants except absorbance (no monthly trend was applied, by design, because traffic-based absorbance was not thought to vary by season) as described in Table 2.1.

We were also able to incorporate some 'mobility' indicators into the land-use regression model estimates in this study, using the time-activity log and GPS route data. Thus, we generated land-use regression exposure estimates based on home location only (i.e. assuming the subject spent 100% of time at home), home+work locations (weighted by the percentage of time spent at home and work from the participants' time-activity log, i.e. assuming that the combination of home and work time summed to 100% of total), and estimates based on the detailed GPS route data (taking into account the full range of locations that each participant followed during a testing session). This last was done by extracting the land-use regression model values for every GPS route point and then averaging the time-weighted land-use regression estimates for every GPS point in a route. This approach reflects all of the subjects' mobility (as recorded by the GPS unit) during their sampling session and was only used for sampling sessions with close to complete GPS route data (n=35). To determine 'complete routes' we calculated time gaps between each GPS point (latitude and longitude). Routes were excluded if there were large time gaps (>16 hours) or, a combination of space and time gaps between points. Average GPS signal precision in this study was +/- 30 m on when the signal was established.

Two sets of home and home+work estimates were generated: one set based on location addresses and the other based on location postal codes.

Exposure estimates using ambient monitoring data

We extracted hourly $PM_{2.5}$, NO and NO_2 measurements from all municipal air monitoring stations within 50 km of the subjects' homes (25) (11 stations for NO/NO_2, 6 stations for $PM_{2.5}$).

Two spatial methods were used to assign ambient data to individual subjects' home postal codes. The first method simply assigned values from the nearest monitoring station to the subjects' location. The second used an inverse distance weighted approach to combine the nearest 3 monitoring stations to the subject. Visual representations of the annual averages for all postal codes in the study area using these methods are shown in Figure 2.2. Exposure estimates were averaged over all days in a 14 day window on either side of the sampling session to generate a "monthly" estimate. A summary of all the exposure estimation methods and their spatial and temporal averaging components is shown in Table 2.1.

Data analysis

Data were analyzed using SAS-PC v 9.1 (SAS Institute, Cary NC).

All personal measurements were positively skewed and were log-transformed for analysis. Incomplete samples (pump failure, etc) were excluded but other data collected during the session were still analyzed provided the subject had not modified their activities or abandoned the sampling equipment due to the failure. Field blanks showed no substantial contamination for any samples, so no corrections were applied. Samples below the limit of detection (LOD) were assigned a value of $\sqrt{2} \times (LOD)$ (26).

We compared all (log-transformed) personal measurements against land-use regression and ambient exposure estimates, with and without mobility adjustments, using Pearson's r correlations. For simple descriptive analyses and when examining correlations, we treated each sample as independent (i.e. did not make any adjustments for repeated samples on the same subject).

We created linear regression models for each pollutant with personal exposure (log-transformed) as the dependent variable, using mixed effects models, to examine the ability of exposure estimates to explain different components of the variability (between and within subject) in personal measurements while controlling for repeated measures among subjects.

The land-use regression and ambient exposure estimates were examined in the regression models as individual predictors (fixed effects) with subject included as a random effect. Results from the final models were compared to baseline (subject only) model. We examined how much of the between and within subject variance was explained by the exposure estimates when compared to the baseline model.

The final multivariable models for the log-transformed measured pollutant values (Y^*) was of the form

$$\ln(y) = Y_{ij}^* = \beta_o + \varepsilon_{ij} + \beta_1 x_{ij} + \sum b_n x_n$$

where j is the j-th measurement, i is the i-th subject, and n is the number of subjects. The mean intercept of all subjects (the average background measured pollutant level) is βo, and β_1 is a fixed effect coefficient. The random intercept values b_n are multiplied by a placeholder x_n indicating the presence of that subject in the model. The random intercepts (b_n) are the difference between the subjects' intercept and the group mean intercept βo. The model assumes that errors (ε_{ij}) are normally distributed with a mean of zero and within subject variance component σ^2_{WS} and subject random effects are also normally distributed with between subject variance component σ^2_{BS}.

Finally, because many epidemiologic studies use categorized exposure estimates rather than individual level data, we also examined characteristics of the personal exposure measurement data, by quartile, using quartile cutpoints based on quartiles of the exposure estimate distributions.

Results

Of the 62 women enrolled in the study, 55 completed 2 or more samples, 7 completed one sample only (miscarriage, early delivery, moving out of the study area, unknown reasons). Subjects with only one sample were still included in the analysis. Subjects were primarily white (82%), mean age was 32 years, highly educated (90% university educated) and median family income category was $60-80,000 /year. A total of 127 samples were collected between October 2005 and August 2006 (32% in winter, 39% in spring, 17% in summer and 13% in fall).

Exposure estimates for all methods are shown in Table 2.2. Only one personal NO sample was below the limit of detection. Since land-use regression exposure estimates based upon addresses were very highly correlated with those based upon postal code estimates for all pollutants (Home: Pearson's r= 0.96-.99' Work: Pearson's r= 0.87-.97) only postal code results are presented as postal code information is more commonly available for population-based cohorts. Estimates based on ambient monitoring using the nearest monitor were very similar to those based on inverse distance weighting (IDW) of three monitoring stations; therefore results are reported for IDW only.

Measured personal exposures were higher and more variable than land-use regression for all pollutants except NO or ambient exposure estimates (paired t-tests showed positive mean differences, $p<0.005$, for all pollutants, except NO_2: no significant differences for LUR and negative mean difference ($p<0.0001$) for ambient NO_2). Land-use regression estimates had greater variability and covered a wider range compared to the ambient estimates, which is expected since land use regression has much higher spatial-level variability.

For the 35 samples with complete GPS route data, the percentage of time spent at home and at work, calculated using GPS data, was highly correlated with percentage estimates based on activity logs (r=0.96 for home and 0.88 for work). Given that some participants worked at home but still coded their activities as "work" this may account for the observed lower correlation for work activities. Similarly, for this same subset, mobility adjusted land-use regression exposure estimates (using the full GPS route data) were highly correlated with the home only estimates (r= 0.83-0.92) and very highly correlated with the home+work estimates (r=0.94-0.98), for all pollutants.

Table 2.2 shows simple correlations between personal monitoring results and each of the following exposure estimates: estimates based on ambient monitoring (monthly, with inverse distance weighting) and land use regression (home and home+work estimates). The only pollutant showing these correlations in the moderate range was NO (r= 0.49-0.55); this was the case for all approaches to exposure estimation (land-use regression and ambient).

Mobility effects

Land-use regression exposure estimates using home and work locations were slightly more highly correlated with personal measurement (Table 2.3) for NO, NO_2 and $PM_{2.5}$. For the subset of data with full GPS routes, using the complete route-based land-use regression estimates showed only slight improvement over the home+work estimates when compared to personal measurements (NO: home+work r=0.77, GPS r=0.78; NO_2: h+w r=0.57, GPS r=0.66; absorbance: not significant; $PM_{2.5}$: h+w r=0.45; GPS r=0.47). Strangely, the correlations were stronger for all pollutants when considering just the GPS subset. After further investigation, we noted that on sampling sessions where GPS route data was useable, subjects spent significantly more time at home than on the sessions without GPS route data. When stratifying to subjects spending more time at home (>65%), the personal measurements and land-use regression estimates were more highly correlated than with the whole group (Table 2.3).

Results from the mixed effect regression models are shown in Table 2.4. These results are displayed to show the comparison of the proportion of variability in personal measurements explained by the various exposure estimate 'predictors'. As was seen in the simple correlation analyses (Table 2.3), the greatest percent of baseline variance in personal exposure explained by the exposure estimates was for the NO models (24-38% of total variance).

Since the land-use regression approaches are intended to detect within-city spatial differences in exposure, we focus these regression results on the between subject variance component (Table 2.5). The within subject variance in the land use regression estimates is only due to temporal shifts in ambient pollution (unless the subject also moved during sampling). In the case of NO, mobility (home+work estimate) explained 20% of the between subject variance compared to a baseline (subject only model); whereas home only explained 4%. Similarly for NO_2, including mobility explained more variance than home only (7% home+work, 2% home only), but the NO_2 models explained only a small fraction the total variability. The $PM_{2.5}$ and absorbance results confirm that modest correlations seen in Table 2.3 are clearly due to within subject differences.

Comparing exposure distributions (personal measurements v. land-use regression) by category (quartile)

Table 2.5 shows geometric mean values for personal measurements in quartiles, where quartile cutpoints were determined by the land-use regression model estimate (home only). Results show significant increases in the geometric mean NO by quartile (kruskal-wallis test $p<.0001$). There was a 38 ppb increase in geometric mean NO value between the lowest and highest quartile groups, representing a similar increase in land-use regression estimate (about 44 ppb). None of the other pollutants showed significant differences by quartile, but increasing trends were observed for both NO_2 and $PM_{2.5}$.

Similar results were seen in examining the fixed effect values obtained from the regression models (Table 2.6). This table shows the predicted change in the personal measurement (dependent variable) for a change in the exposure estimate variable (independent) adjusted to the interquartile range (25^{th} to 75^{th} percentile) of that independent variable. Because the dependent was log-transformed, the magnitude of the effect estimate is a percentage change. For example, as shown in the table, there was a 61% change in personal NO measurements for an increase of about 25 ppb (interquartile range) in land-use regression estimate at home, and 7% change for NO_2. In the quartile analysis (Table 2.5), the trend from 2^{nd} to 3^{rd} quartile (NO) showed an increase from 28 ppb to 43 ppb (about 65%).

Results in Table 2.5 and Table 2.6 suggest that land-use regression estimates were not significant in predicting category changes in personal concentrations for $PM_{2.5}$ or absorbance in regression models. By contrast, outdoor ambient monitor-based exposures were associated with significant changes in personal measurements for all pollutants except NO_2.

Comparing Pollutants

Overall, estimates for NO performed best at explaining the spatial (between subject) variability in personal exposure in this population. For NO_2, annual land-use regression explained a modest amount of the spatial variability only. In comparing the ability of ambient monitoring to predict personal measurements for different pollutants, ambient NO explained more of the between subject variance than ambient $PM_{2.5}$ (Table 2.4).

Discussion

Various studies have demonstrated large spatial variability in air pollutant concentrations between cities (27,28), between urban and rural areas (29), and from proximity to roadways (30). Fixed-site monitoring approaches capture spatial variability at the between city or urban background level whereas land-use regression models were developed specifically to reflect within-city variability, especially that resulting from proximity to traffic. A recent evaluation of the use of limited numbers of fixed-site city-level ambient monitors to predict population exposure to air pollution in France showed little association between fixed site and personal measurements and called for caution in using monitor-based approaches in epidemiological studies of long-term exposure (those exploiting spatial contrasts) (31-33). However, fixed-site approaches are widely used in many study designs, especially those utilizing temporal and regional-level spatial variability. Land-use regression models clearly reflect smaller-scale spatial variability but there are no previous studies demonstrating how well these models capture actual differences in personal exposures.

Evaluation of land use regression estimates

Focusing on land-use regression, which has never been evaluated against personal sampling, we saw a strong significant trend in mean personal exposures between quartiles of predicted home-based values for NO (Table 2.5) and moderate correlations. The trend was comparable to fixed effect estimates from the regression models where we controlled for repeated measures among subjects. For NO_2, only annual average land-use regression values were modestly associated with personal results indicating that personal NO_2 exposure was most strongly affected by spatial contrasts and less by temporal variability in regional ambient background concentrations.

While both NO and NO_2 land use regression models were developed using the same number of samples, only NO showed a strong relationship with the personal measurements in this study. Considering only the annual land-use regression values, NO had much greater spatial variability (higher SD) than NO_2. The images of the surfaces (Figure 2.1) also show less distinct spatial variation for NO_2 than NO (less transitions in colour/shading), as expected given that NO_2 requires atmospheric transformation, whereas NO is a primary emission. Because the traffic relationship for NO_2 is relatively weak compared to NO, we suspect that the NO_2 signal from traffic is being hidden by the effects of indoor sources and lower spatial variability.

We saw little relationship between personal measurements and land use regression estimates for particulate pollutants (absorbance, $PM_{2.5}$). Since no other personal monitoring studies have evaluated land-use regression models, it is difficult to compare our result to other studies. The land-use regression surfaces for NO and NO_2 were developed using a total of 114 measured samples collected throughout the study area whereas the $PM_{2.5}$ and absorbance surfaces were developed using only 25 samples due to the increased cost of $PM_{2.5}$ sampling. In addition, the regression model R^2 were higher (R^2: NO=0.62, NO_2=0.56; $PM_{2.5}$=0.52; Absorbance=0.39) for the NO/NO_2 surfaces suggesting that these pollutants were better modeled by geographic variables (22). Since the $PM_{2.5}$ and absorbance land-use regression surfaces were based on relatively sparse data and poorly validated by ambient measurements (when the original surfaces were developed), it is unsurprising that we were unable to see a relationship with these data and personal measurements.

Using methods other than land-use regression, several studies have demonstrated that differences in traffic intensity and/or living near a busy road can be correlated with personal measurements of NO, NO_2 and/or absorbance. Van Roosbroeck et al. found an increase of 77% (unadjusted for indoor sources) in home outdoor NO and 38% in personal absorbance for the effect of living near a busy road in a study of 40 children in the Netherlands. Living near a busy road was defined as being within 75 m of a road with traffic volume of 10,000 cars/day. To compare our results to this study in the Netherlands, we examined the group whose home location was within 75 m of a road with traffic volume >15,000 cars/day (15 women, 27 measurements out of 127 total). We found small and non-significant increases in arithmetic means for NO (47.2 vs. 53.3 ppb) and NO_2 (18.2 vs. 20.7 ppb) for living near a busy road in Vancouver. We found no trends for personal $PM_{2.5}$ or absorbance. Our inability to detect a strong trend for proximity to roads may be due to the relatively few subjects living in close proximity to busy roads in this study. In addition, distance to road was confounded by building type; high-rise or large multi-unit buildings were on average 150 meters closer to busy roads than smaller buildings (p=0.003). Similarly, those living more than 4 floors above ground were also closer to busy roads. Others have shown that ground-level pollutant concentrations can decrease significantly at higher elevations around high-rise buildings (34).

Evaluation of ambient measurements

In this study, fixed-site monitoring (interpolation using IDW) of NO and $PM_{2.5}$ showed some ability to predict personal measurements for NO, absorbance or $PM_{2.5}$ either in pooled correlations or regression models. The results of the mixed models (Table 2.4) analyses show that most of the variance explained by ambient estimates was due to temporal correlations between subjects and ambient data (within subject variance component). In the case of NO, we saw a small amount of between subject (spatial) variance explained by the ambient monitoring data. This is likely due to the dense monitoring network in the study region (N=11 monitors) and the relatively strong intraurban spatial variability that was captured by the monitoring network. Ambient $PM_{2.5}$ explained no spatial variability between subjects; all variance explained was temporal or within subject. This result for $PM_{2.5}$ is unsurprising given both the lower within-city variability of ambient $PM_{2.5}$ (23) and the relatively few (N=6) monitoring stations available for interpolation. Based on these results, we conclude that ambient monitoring stations were relatively poor predictors of spatial variability in personal exposures for all measured pollutants except NO, but good predictors of temporal variability.

The inability of regulatory network monitor-based methods to capture spatial variability between subjects has been shown in other studies. When attempting to use monitoring stations to capture spatial variability, we consider cross-sectional comparisons between personal concentrations and ambient data. A study in 3 French cities among school-aged children reported very low raw correlations between ambient NO_2 and personal exposure (r=0.01-0.04) depending on the city (33). Since no repeated samples were collected for subjects it was not possible to examine differences between spatial and temporal variance components. In this study personal measurements were also compared to a traffic-based exposure index (ExTra index) based on traffic and geographic data (35) rather than including measurement data as in land use regression. Of the total variability in personal NO_2 explained in regression models (including indoor sources such as ETS), ambient NO_2 pollution explained much less of the variance than the traffic-based index. For $PM_{2.5}$, the reverse was found; ambient $PM_{2.5}$ explained more variance than the traffic based index (32). These results are similar to our findings as we also found that ambient concentrations of NO_2 poorly represent personal measurements; whereas traffic-based measures may represent some of the spatial variability. By contrast, ambient $PM_{2.5}$ was more strongly related to personal measurements than our land-use regression surfaces likely because of the strong temporal correlations between ambient levels and personal measurements.

While we had repeated samples per subject, we still had relatively low longitudinal correlations with ambient data when compare to other studies. Very high correlations have been shown in panel studies with larger numbers of repeat measurements. For example, a study in the Netherlands (36) found strong correlations (median spearman rho=0.91 (absorbance) and 0.7 ($PM_{2.5}$)) between fixed-site outdoor and 24-hour personal measurements (N=36 subjects) measured biweekly over 6 months. Two reasons for the lower longitudinal correlations in our study is that we had few repeated samples (1-3 per subject) and used a monthly average ambient concentration rather than an exact 48-hour average from the sampling day.

Because we were interested in the ability of the estimation methods to detect spatial variability between subjects, we wanted to use comparable temporal information in both methods (i.e. monthly-level). However, in sensitivity analyses, we recalculated ambient estimates for an exact 48-hour window during the sampling session to clarify the impact of temporal trends on personal exposures. Moving to a more time-specific exposure window improved correlations between personal and ambient exposures for NO, $PM_{2.5}$ and absorbance but not NO_2. For example, a greater amount of within subject variance in personal absorbance(6 to 42%) was explained by ambient $PM_{2.5}$ when a more refined time window was used, suggesting that short term ambient fluctuations are especially important for $PM_{2.5}$ exposure assessment.

Comparing ambient vs. land-use regression

A unique feature of this study is the investigation of *both* ambient and land-use regression estimates in comparison to personal measurements. The fact that both estimates were predictive of personal NO is especially interesting given that these two estimates show very different spatial characteristics (Figure 2.1and Figure 2.2). Urban air pollution can be described by a combination of different sources which take effect at different scales. Hoek et al. (37) described three contributions to long-term average exposures: regional (i.e. differences at a 100+ kilometre scale), urban (closer to 10 km scale) and local (within 1 km or less), where local pollution was defined as the direct effect of spatial proximity to traffic sources. Using this approach, we suggest that land use regression estimates approximate local and urban pollution while ambient monitoring approximates a combination of the regional and urban component. Hoek et al argue further that contributions from each of these sources should be estimated separately and then combined to approximate long-term exposure. The results from this study showing that both local and urban level sources are contributors to personal measurements in this population lend further weight to this argument.

Importance of mobility

There have been calls for increased use of mobility and time-activity patterns to improve exposure assessment (38). When we analyzed the subset of subjects spending more time at home on the sampling day, the (personal to home-only land-use regression) correlations were stronger with increasing time spent at home. This supports the use of land-use regression as a proxy for home exposure, especially for populations like seniors who spend a greater time at home. Including work locations as well as home location did improve our ability to estimate personal exposures so we conclude that a non-home secondary location can be of critical importance in developing exposure estimates. Our population may have had more varied activity patterns than the general population since most women did not have traditional 8-hour/day work schedules. Nevertheless, we still found that including work location increased our ability to predict personal measurements. For more traditional working or school-going populations, including work or school as well as home locations in exposure assessment could have an even greater impact.

Previous authors have argued that transit-time exposures are especially important because they usually occur during peak pollution times and on or near roadways (21). This study has attempted to address this question using the subject specific GPS-based estimate and the land-use regression surfaces. When we used complete mobility data (using GPS) we saw little change in comparison to personal monitoring as compared to estimates based on home + work address. It is difficult for us to comment on the influence of transit mobility on personal exposures in our study since the GPS technologies did not work well for the most mobile segment of our population[1]. We did examine time spent in motorized and non-motorized transit as a predictor variable in univariate and multiple regression analyses (results not shown) and it was not associated with personal exposures.

One of the limitations of this study is that the measurements were from a non-random sample of pregnant women. There is no reason to suspect that their exposure estimates were biased but it is possible that personal measurements in this population may have been modified by activity patterns specific to this population of pregnant women. Sampling was week-day only and unevenly distributed across 4 seasons although we have relatively even coverage of heating and non-heating seasons. We also compared $PM_{2.2}$ to ambient and land-use regression estimates of $PM_{2.5}$, although we do not expect substantial bias from this difference in measurements. We also compared snapshot measurements (48-hour) to exposure models designed for chronic exposure studies (land-use regression). Because of the short sample time and relatively few repeats per person, this is an imperfect evaluation of the spatial differences in the model when used for long-term exposure

[1] A simulation of exposure at locations *other* than work or home is shown in Appendix C. This estimated the %error in modeled exposure from ignoring the *other* exposure locations.

assessment. Also, differences between the measurement methods used for the fixed sites (monitor-based models) and personal measurements may have contributed to the unaccounted for variability in the models.

This study is the first to evaluate land use regression models as predictors of personal exposure in any study population and for both primary and secondary pollutants. The unique focus on personal exposures of pregnant women has also increased exposure data for this potentially vulnerable population. We found that models using both land-use regression (NO and NO_2) and fixed-site monitors (NO, absorbance, $PM_{2.5}$) showed the strongest ability to predict personal measurements. Including mobility based on work location did improve exposure models. Lastly, we discussed the importance of temporal and spatial variability in exposure models and their relationship with personal measurements.

When considering exposure assessment methods to be used in future air pollution epidemiological studies, it is important to understand the relevant time-frame of the exposure of interest. For example, for chronic exposure studies a land-use regression model could be combined with a yearly trend based on ambient data. The combination of land-use regression and monthly or yearly time-trends presented in this paper is relatively novel and was developed for a study of birth outcomes which required an intermediate-length exposure window. For short-term exposures where temporal variability is of interest, then ambient monitor-based methods could be more useful.

Figures and Tables

Figure 2.1 Vancouver Annual Average Land Use Regression Surfaces ***(shown for study area)***

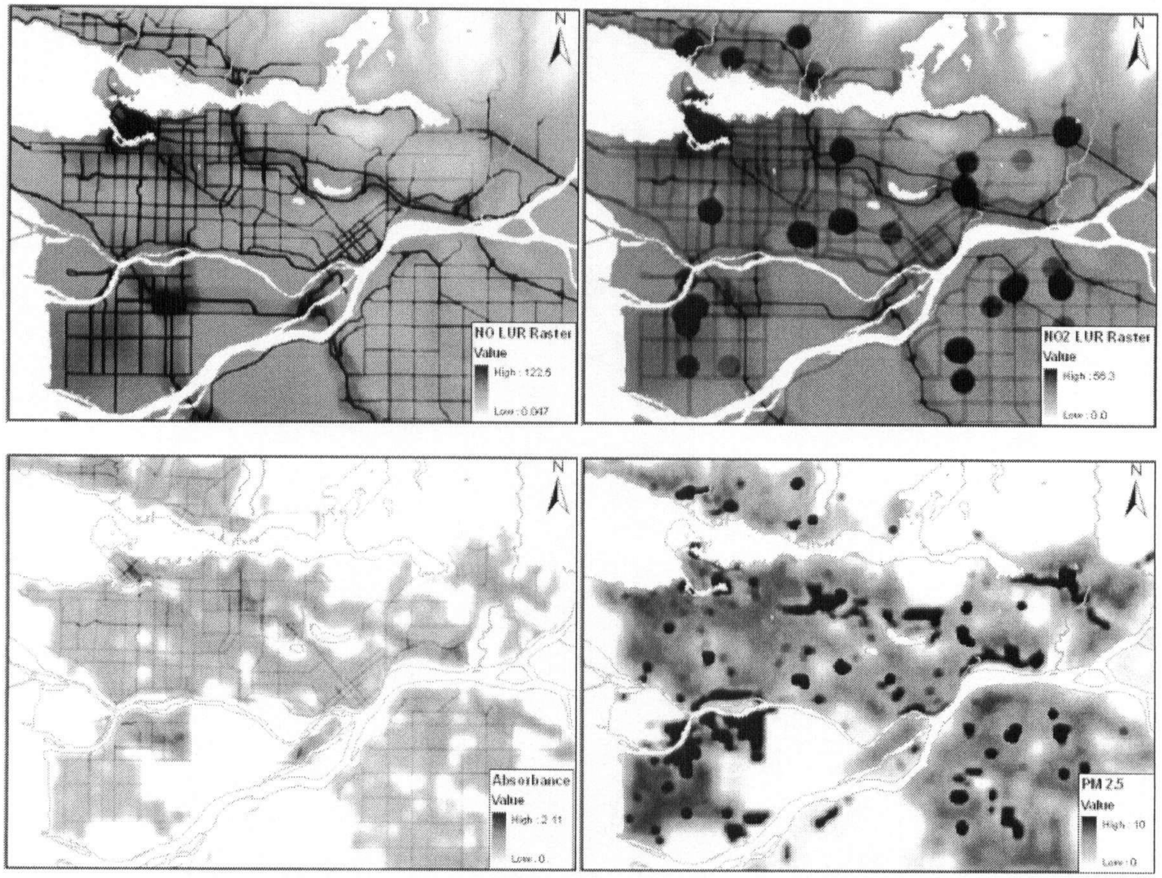

Figure 2.2 Annual Average Ambient Monitoring NO Estimates using Nearest Monitor and IDW

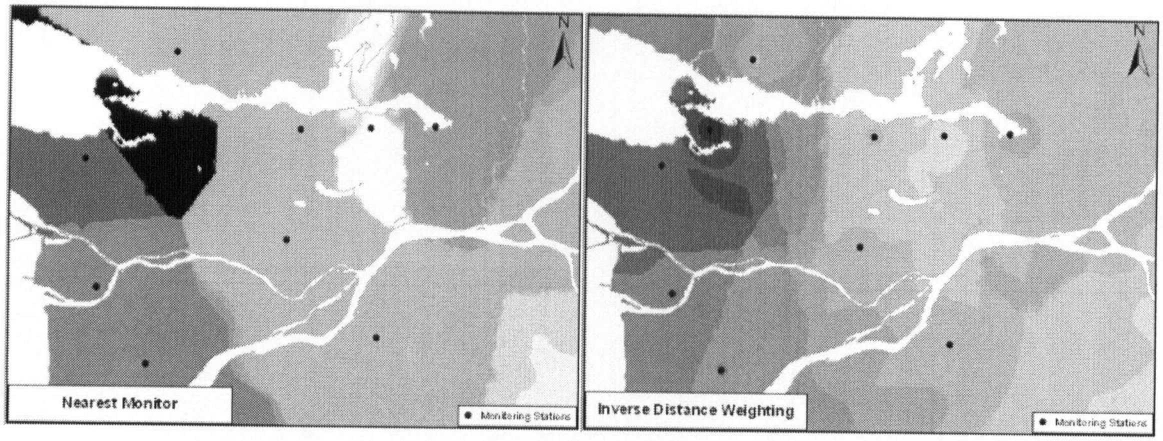

Table 2.1 A guide to the exposure estimation methods and their spatial and temporal averaging

Exposure Estimation Method	Temporal Averaging	Spatial Averaging
Personal sampling	48 hours	Integrated sample over all locations for the subject when the sample was collected
Land Use Regression Home	Monthly[1] Annual	Average for subjects' home postal code location based on LUR (has about a 50 m. spatial resolution, see Figure 2.1)
Land Use Regression Home+Work	Monthly Annual	Time-weighted average of home and work postal code locations based on LUR (has about a 50 m. spatial resolution, see Figure 2.1)
Ambient Monitoring (Nearest Monitor)	Monthly 48-hour[2]	Distance to nearest monitoring stations (about 10 km on average) (see Figure 2.2)
Ambient Monitoring (Inverse Distance Weighting)	Monthly 48-hour[2]	Average of 3 nearest stations, weighted by distance – gives a spatial resolution that varies with monitor density (see Figure 2.2)

[1] No monthly averaging for absorbance.

[2] Ambient 48-hour results not shown; described as sensitivity analysis in the Discussion.

Table 2.2 Exposure estimates based on personal sampling, land-use regression and ambient methods

Estimated Exposure	Method	Arithmetic Mean (Std Dev)	Geometric Mean (GSD)	Min - Max	IQR
NO (ppb)	Personal sampling	48.5 (50.3)	36.8 (2.0)	6.9 - 474	36.3
N=128	LUR[1] Home (Monthly)	27.0 (19.7)	21.4 (2.0)	3.6 - 146	25.5
	LUR Home+Work (Monthly)	28.0 (18.4)	23.2 (1.9)	6.0 - 134	24.7
	Ambient IDW[2]	17.6 (14.5)	13.9 (1.9)	4.2 - 83	13.0
NO_2 (ppb)	Personal sampling	18.7 (9.1)	16.9 (1.6)	4.8 - 76	10.7
N=128	LUR Home (Annual)[3]	17.3 (3.3)	16.9 (1.2)	6.5 - 28	2.8
	LUR Home+Work (Annual)	17.4 (2.9)	17.2 (1.2)	7.6 - 27	2.5
	Ambient IDW	19.6 (4.0)	19.2 (1.2)	10.8 - 27	6.9
Absorbance (10^{-5} m^{-1})	Personal sampling	0.9 (0.4)	0.8 (1.5)	0.2 - 2.4	0.5
N=120	LUR Home (Annual)[4]	0.7 (0.3)	0.7 (1.7)	0.0 - 1.2	0.2
	LUR Home+Work (Annual)	0.7 (0.2)	0.7 (1.7)	0.1 - 1.3	0.2
	No ambient data.				
$PM_{2.5}$ (µg/m^3)	Personal sampling[5]	11.3 (6.6)	10.0 (1.6)	4.2 - 45.3	5.7
N=124	LUR Home (Annual)	4.2 (1.5)	4.2 (1.4)	0.0 - 10.1	1.5
	LUR Home+Work (Annual)	4.0 (1.3)	3.7 (1.6)	0.3 - 7.5	1.3
	Ambient IDW	4.8 (1.3)	4.6 (1.3)	2.6 - 9.9	1.8

[1] LUR=Land use regression surfaces as described in (22) and that were developed based on road length metrics.

[2] IDW=Inverse distance weighted concentrations from the 3 closest ambient network monitors.

[3] In the analyses, annual NO_2 showed the strongest relationship to personal measurements (rather than monthly), so only annual results are reported in the descriptive tables.

[4] No monthly trend was applied to the absorbance estimates by design in the development of the land-use regression surface for this pollutant.

[5] Personal sampling for particulate was collected as $PM_{2.2}$ not $PM_{2.5}$

Table 2.3 Correlations between personal measurements and exposure estimates (same pollutant, except absorbance as noted) for all subjects and subset with >65% of time spent at home.

Personal Measurements* (log-transformed) Compared to Exposure Estimates:	Pearson's r Correlations			
	NO-NO (n=128)	**NO_2-NO_2 (n=128)**	**Abs-$PM_{2.5}$ (n=120)**	**$PM_{2.2}$- $PM_{2.5}$ (n=124)**
LUR Home[1]	0.49	0.18	*-0.11 (n.s.)*	*0.07 (n.s.)*
LUR Home+Work	0.55	0.28	*-0.10 (n.s.)*	*0.10 (n.s.)*
Ambient IDW Monthly	0.54	*0.05 (n.s.)*	0.29[2]	*0.12 (n.s.)*
subset with >65% of total sampling session spent at home (n=61)	**NO-NO**	**NO_2-NO_2**	**Abs-$PM_{2.5}$**	**$PM_{2.2}$- $PM_{2.5}$**
LUR Home	0.72	0.26	*-0.19 (n.s.)*	0.30
LUR Home+Work	0.72	0.26	*-0.14 (n.s.)*	0.29
Ambient IDW Monthly	0.59	*0.06 (n.s.)*	0.34	*0.10 (n.s.)*

[1] Land use regression values for NO and $PM_{2.5}$ are monthly averages, whereas absorbance and NO2 are annual averages.

[2] Personal absorbance was compared to ambient $PM_{2.5}$, since no ambient absorbance measurements were collected

Table 2.4 Models predicting personal measurements using outdoor ambient exposure estimates and controlling for repeated measures on subjects.

Model description (random and fixed effects)	Variance component (95% Confidence Limits)		% Variance explained[1] (compared to baseline)		
NO Personal (dependent)	**Within Subject (σ_{ws}) (temporal)**	**Between Subject (σ_{BS}) (spatial)**	σ_{ws}	σ_{BS}	**Total**
Baseline (Subject only)	0.332 (0.242 ,0.485)	0.188 (0.101 ,0.470)			
+ LUR NO Home	0.214 (0.156 ,0.312)	0.180 (0.107 ,0.366)	36	4	24
+ LUR NO Home+Work	0.210 (0.153 ,0.306)	0.151 (0.086 ,0.327)	37	20	31
+ Ambient IDW NO	0.208 (0.152 ,0.304)	0.162 (0.094 ,0.343)	37	14	29
NO_2 Personal (dependent)					
Baseline (Subject only)	0.087 (0.063 ,0.126)	0.112 (0.072 ,0.202)			
+ LUR NO_2 Home (Annual)	0.086 (0.062 ,0.125)	0.110 (0.070 ,0.199)	1	2	2
+ LUR NO_2 Home+Work (Annual)	0.084 (0.061 ,0.122)	0.104 (0.066 ,0.190)	3	7	6
+ Ambient IDW NO_2	--				
Absorbance Personal (dependent)					
Baseline (Subject only)	0.165 (0.118 ,0.246)	0.025 (0.006 ,1.341)			
+ LUR Absorbance Home	--				
+ LUR Absorbance Home+Work	--				
+ Ambient IDW $PM_{2.5}$	0.146 (0.105 ,0.219)	0.029 (0.009 ,0.422)	11	-19	8
$PM_{2.2}$ Personal (dependent)					
Baseline (Subject only)	0.169 (0.121 ,0.251)	0.060 (0.026 ,0.251)			
+ LUR $PM_{2.5}$ Home	--				
+ LUR $PM_{2.5}$ Home+Work	--				
+ Ambient IDW $PM_{2.5}$	0.154 (0.110 ,0.230)	0.075 (0.036 ,0.230)	9	-25	0

[1] Percent of variance explained from significant models (between and within subject) represents the amount of spatial and temporal variability, respectively, in personal measurements explained by the model effects.

Table 2.5 Mean personal concentrations (pooled from all samples) by quartile of land-use regression (LUR) exposure estimates at home and results of significance tests for differences between quartiles[1]. N=29 to 33 measurements per quartile depending on the pollutant.

	Geometric Mean (GSD)					Anova	K-w
LUR Quartiles	**1st**	**2nd**	**3rd**	**4th**	P^2	**p-values**	
NO (ppb)	24.8 (1.9)	27.9 (1.6)	42.4 (1.8)	62.3 (2.1)	** / **	<.0001	<.0001
NO_2 (ppb)	15.0 (1.7)	17.1 (1.6)	20.0 (1.3)	16.1 (1.5)	/ *	0.0680	0.0367
Absorbance (10^{-5} m^{-1})	0.8 (1.5)	0.8 (1.6)	1.0 (1.5)	0.7 (1.5)	* / *	0.0110	0.0171
$PM_{2.2}$ (μg/m^3)	9.7 (1.6)	9.4 (1.5)	10.3 (1.6)	10.8 (1.8)		0.7002	0.7674
Ambient Quartiles							
NO (ppb)	24.3 (1.8)	28.7 (1.8)	44.6 (1.9)	60.1 (2.0)	** / **	<.0001	<.0001
NO_2 (ppb)	16.3 (1.7)	17.6 (1.6)	16.9 (1.6)	17.1 (1.4)		0.9213	0.8409
Absorbance (10^{-5} m^{-1})[3]	0.76 (1.5)	0.79 (1.5)	0.82 (1.5)	0.91 (1.7)		0.4007	0.3641
$PM_{2.2}$ (μg/m^3)	9.54 (1.7)	9.84 (1.6)	10.0 (1.6)	10.8 (1.6)		0.7700	0.6570

[1] NO and $PM_{2.5}$ results use monthly LUR quartiles; NO_2 and absorbance use annual LUR quartiles.
[2] P-values symbol: Anova / kruskal-wallis p-values, with p<0.01=**, p = 0.01 to 0.1=*, otherwise blank
[3] Absorbance shown by quartiles of ambient $PM_{2.5}$

Table 2.6 Percentage increase in personal measurements as predicted by mixed effect models for a change in exposure estimate from the 25th to 75th percentile (Interquartile range or IQR).

IQR for LUR methods: NO=25 ppb, NO_2=2.8 & 2.5 ppb; IQR for ambient: NO=13 ppb; $PM_{2.5}$=1.8 μg/m³.

Personal Measured Pollutant	Percentage increase in personal measurements for change from 25th to 75th percentile of outdoor exposure estimate (95% confidence interval)[1]		
	LUR		Ambient IDW
	Home	Home+ Work	
NO	61 (41, 83)	68 (48, 91)	41 (29, 53)
NO_2	7 (-1, 15)**	11 (3, 19)	--
Absorbance	--	--	18 (7, 31)
$PM_{2.2}$	--	--	12 (0, 24)**

[1] All effect estimates were significant at p<0.0001 except **= p<0.1 and *= p<0.13

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Chapter 3 Predicting personal exposure of pregnant women to traffic-related air pollutants[1]

Introduction

Epidemiologic studies have demonstrated that increased maternal exposure to air pollutants, including those arising from traffic, may increase the risk of adverse birth outcomes (1-4).Reducing this risk can be critical in preventing disease later in life. For example, low birth weight babies can have an increased lifelong risk of disease, impaired immune function, learning disabilities or higher incidence of diabetes (5). Increasing evidence suggests that there are critical periods in the development of the fetus where exposure to environmental toxicants may lead to adverse birth outcomes (6).

Epidemiological research on air pollution and birth outcomes is challenged by a common difficulty in studying large populations, accurately assessing exposure to air pollutants. A recent improvement in exposure assessment using traffic indicators has been the development of land-use regression models (7,8) that capture a high level of spatial variability, can be used for population-studies, yet estimate exposures at an individual level. Increasing our understanding of the variety of factors that influence personal exposure to air pollutants for pregnant women may lead to improved exposure assessment for use in large-scale epidemiological studies in which individual measurements are not feasible. Similarly, understanding how estimates of outdoor pollution using traffic-based pollution models such as land-use regression interact with individual-level determinants may also inform population level exposure assessment.

To investigate associations with birth outcomes, it is most useful to specifically assess exposures of pregnant women, a segment of the population for which there is very little specific exposure data. If activities of women during pregnancy are different than activities of other population groups, then their exposures may differ as well. Similarly, factors that influence exposure may be unique to this

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[1] A version of this chapter will be submitted for publication.

population. Few studies have assessed personal air contaminant exposures of pregnant women. A personal monitoring study in Poland (9) reported on sources of variability of fine particulate ($PM_{2.5}$) exposure among a group of pregnant women. This study identified background ambient PM_{10}, environmental tobacco smoke, coal/wood heating and industrial plant proximity as determinants of personal exposure to $PM_{2.5}$. A second study measured personal polycyclic aromatic hydrocarbons (PAH's) among pregnant minority women in New York City (10). This study found time spent outdoors, residential heating and indoor burning of incense to be associated with personal PAH exposures. Neither of these studies evaluated the use of land use regression estimates of outdoor air pollution concentrations, methods that are believed to better capture within-city variability in concentrations relative to use of regulatory monitoring data.

In this study, we conducted personal measurements and collected individual-level activity, mobility and demographic data on a sample of pregnant women in Vancouver, Canada. We also estimated their ambient outdoor exposure using two different methods: concentrations at home plus work locations interpolated from the regulatory air monitoring network; and land-use regression models of traffic-related air pollution. By including both individual-level factors as well as estimated outdoor pollutant levels we can assess the relative importance of these other factors in predicting personal exposures for this population. Secondly, we can identify sources of variability within and between subjects, and potential areas of concern to target for exposure reduction.

Methods

Study Design

The study was conducted among a non-random sample of 62 pregnant women from the Vancouver metropolitan area from October 2005 to August 2006. Eligible subjects had healthy, low-risk pregnancies and were non-smokers living with non-smokers. The study protocol and material was approved by the University of British Columbia Behavioural Research Ethics Board. Recruitment methods have been reported elsewhere (Chapter 2). This study was a component of the exposure evaluation for a cohort study (120,000 births) of air pollution impacts on births (11).

Sampling Methods

Personal monitoring was conducted over 48-hour "sampling-sessions", ideally spaced 3-months apart during each trimester of pregnancy. Sampling sessions were conducted on weekdays only. Due to the difficulty of recruiting women in their first trimester, most subjects were in their second trimester and were asked to complete two measurements. We collected personal samples of nitric oxide, NO, and nitrogen dioxide, NO_2, fine particles and fine particle filter reflectance (converted to absorbance measurements), as an indicator of elemental carbon or absorbance. During each session, subjects kept a time-activity log of locations and activities on 30 minute intervals. On the first sampling session, women completed a (technician-administered) home and work building characteristics questionnaire and a questionnaire describing personal characteristics.

The personal air monitoring equipment was contained in a small backpack or shoulder bag. The monitors were attached to the shoulder strap of the bag to fit approximately in the subject's breathing zone. We encouraged women to wear the sampler while moving about and to place the equipment on a table or chair near their current location when sitting. At night, the women were advised to place the sampler outside the bedroom if the noise was disturbing to them.

We measured personal particulate matter (PM) with Personal Environment Monitors (PEM, MSP Corporation) (12). A $PM_{2.5}$ PEM was loaded with a pre-weighed 37-mm 2um-pore size Teflon filter connected to a battery powered sampling pump (Leland Legacy, SKC Inc.) set to a flow rate of 5 L/min. Flow rates were measured pre and post-sampling with a primary flow meter (DryCal DC-Lite, Bios International Corporation). We collected at a flow rate that was higher than designed to collect a $PM_{2.5}$ sample resulting in a 50% cutpoint of about 2.2μm. Since the study was designed to focus on absorbance (a marker of elemental carbon), the use of $PM_{2.2}$ should not affect the mass of the target agent, which is dominated by fine particles (13,14). Elemental carbon particles typically have a mass distribution peak from 0.1 to 1.0 μm, which is smaller than both sampler cut-offs (15). We measured filter mass in triplicate pre- and post-sampling in a temperature (23 °C, SD=0.77 °C) and humidity-controlled room (34%, SD=3%), using gravimetric methods (balance: Sartorius Micro M3P) and divided the mass by the volume of air sampled to obtain the concentration in air (in $\mu g/m^3$) as described previously (16).

After weighing, we measured the reflectance of each filter using a Smoke Stain Reflectometer (Diffusion Systems Inc.) according to a standard method (SOP ULTRA/KTL-L-1.0 1998).

Previous sampling demonstrated a high correlation between co-located filter absorbance measurements and elemental carbon measurements in the Greater Vancouver area (17,18).

As a final step, the filters were analyzed for levoglucosan (1,6-anhydro-β-D-glucopyranose) using methods described by Simpson et al (19). Levoglucosan is emitted from combustion of biomass and is commonly used as a tracer for wood smoke (20). Levoglucosan measurements were offered as potential effect modifiers in deterministic models of personal (PM and absorbance) measurements with the intent that high levoglucosan measurements would indicate samples influenced by wood smoke.

Personal concentrations of NO and NO_2 were measured using Ogawa passive samplers (Ogawa USA, Inc.). Precoated filters were loaded into cleaned samplers which were stored in airtight sampling containers according to manufacturer's directions until use. The samplers were attached to the strap of the sampling backpack or bag. After sampling, we stored samplers in airtight containers at 4 C until extraction in de-ionized water. The resulting solution was analyzed by ion chromatography to determine nitrite concentration from each coated filter (NO_2 and NO_x). The concentration of nitric oxide, NO, was obtained by subtracting the NO_2 from the NO_x concentrations.

In the time-activity log, subjects recorded their location indoors (at home/work/other), outdoors, or in transit (walk, car, bus, bike or other) during each ½ hour period. Up to two locations could be indicated during each ½ hour period. For each period, the log also requested subjects to note activities such as cooking, smoking exposure, windows open nearby and whether they were wearing the sampler. Using each activity log, we calculated the percentage of time each subject spent in each location or exposed to cooking or smoking and multiplied these by 24-hours to obtain results in terms of hours/day.

The personal questionnaire asked about ethnicity, income, employment type and status, number of other children and their ages. The home and work characteristics questionnaire collected detailed information about building volume (estimated square footage of the building and ceiling height), age, number of rooms, ventilation, heating, gas stove presence, carpeting and presence of an attached garage.

For each subject, we geo-coded their home and work address using ArcGIS/ArcMAP (ESRI Inc) or by manually locating their address using Google Earth. Because geo-coding places addresses directly on road segments, we offset each address point to the center of the appropriately addressed (or nearest) lot using land parcel data from BC Property Assessment (21).

We used two estimates of ambient outdoor air pollution concentrations as potential determinants of personal exposure. One estimate used a traffic-based land use regression model (8) that reflected local street-level variations in ambient outdoor pollution. This model incorporates geographic variables (e.g. road length, population) in combination with measurement data to predict annual average concentrations. A monthly trend was applied to incorporate temporal variation. Outdoor concentrations estimated from the land use regression model were time-weighted using measured activity data and subjects' home and work locations. The second estimate was based on hourly measurements interpolated from regulatory fixed site air monitoring stations (11 stations for NO/NO_2, 6 stations for $PM_{2.5}$) located throughout the study area. We used an inverse-distance weighting method to combine measurements from the 3 nearest monitoring stations to the subjects' home, which were then averaged over the 48-hour sampling session. Because a key focus of the study was to evaluate the land-use regression approach, we tried to include subjects who lived in areas with varying levels exposures according to land-use regression estimates.

Statistical Analysis

All personal pollutant measurements were positively skewed and were log-transformed in the analysis. Some $PM_{2.2}$ and absorbance samples were incomplete due to pump failure, but in these cases samples for NO and NO_2 collected during the same session were analyzed provided the subject had not modified their activities or abandoned the sampling equipment due to the failure. Samples below the limit of detection (LOD) were assigned a value of $\sqrt{2}\times(LOD)$ (22). Questionnaire variables were collapsed if fewer than 5 subjects fell within a category. Certain variables were excluded from analyses due to lack of variability across categories.

All analyses were performed using SAS (SAS Institute, version 9.1.). A mixed-effects regression model was developed for each measured pollutant with subject included as a random effect to account for within-subject correlation between sessions. Because the outdoor ambient pollution estimates showed a strong seasonal component, other potential determinants that were strongly seasonal (e.g. windows open) were not considered in the determinants analysis.

Possible fixed-effect determinants of personal exposures were considered in 5 categories: activity/location (8 variables), home characteristics (16 variables), work characteristics (11 variables), subject demographics (8 variables), and outdoor ambient exposure estimates (3 variables). The levoglucosan measurements were considered as an additional explanatory variable only for absorbance and $PM_{2.2}$. All determinants were initially evaluated as individual predictors of measured pollutant results using linear regression (continuous determinants) and both ANOVA and non-parametric Kruskal-Wallis tests (categorical determinants). The criterion for offering in multiple regression models was $p<0.1$ in the univariate analysis (regression, ANOVA or K-W).

Associations between all independent variables were assessed using correlations (continuous-continuous), analysis of variance (continuous-categorical) and cross-tabulations (categorical-categorical). Variables with $p<0.1$ in ANOVA, unbalanced distributions in cross-tabulations or correlations >0.6 were considered as "similar". For "similar" variables, only the variable with the most significant association (smallest p-value) in univariate modeling with a measured pollutant concentration was entered into the multiple regression model for that pollutant.

A nesting variable was created with a binary status for subjects having or not having a work location. All work building characteristics variables were entered into the models nested under this binary work variable (W).

$$\beta^{*}_{work\,garage} = \beta_{work\,garage} W$$

Variables were offered in the models in groups (categories listed above) to avoid saturating the models. A manual backwards stepwise regression procedure was used first for each group of variables and then for the combination of the variables from each group. Subject was always included in the model, and then, for example, all home characteristics that were non-similar (not associated) were entered. Variables were removed until all home-level parameters had p-values less than 0.1. The same process was repeated for all groups of variables (work, subject demographics, activity/location, outdoor exposures).

The final regression models for the log-transformed measured pollutant values (Y*) took the form shown below where j is the j-th measurement, i is the i-th subject, g is the number of fixed effects in the model and n is the number of subjects. The mean intercept of all subjects (corresponds to the average background measured pollutant level) is β_o, and fixed-effect coefficients, β_n, are multiplied by their values for that variable for the i-th subject on the j-th measurement. The random intercept values, β_n, are multiplied by a placeholder x_n indicating the presence of that subject in the model. The subject random effect values (b_n) are the difference between the subjects' intercept and the group mean intercept β_o.

$$\ln(y) = Y_{ij}^{*} = \beta_o + \varepsilon_{ij} + \sum_{g=1}^{\cdots} \beta_n x_{ij\,g} + \sum b_n x_n$$

The model assumes that errors (ε_{ij}) are normally distributed with a mean of zero and within subject variance component σ^2_{WS} and subject random effects are also normally distributed with mean zero and between subject variance component, σ^2_{BS} . Results from the final determinants models were compared to baseline (subject only) model by examining the variance components.

Influential values were identified using Cook's d (>0.1) and models were tested both with and without them. There was little change in parameter estimates generated both with and without influential values so results are presented for the all data. When highly significant binary variables were identified (i.e., gas stove), we developed separate models for each stratum of the binary variable and compared effect estimates between models. If we saw no major differences in parameters that were included in the final models or in the magnitude or directions of the effects, then only non-stratified models were reported.

Results

Characteristics of the study population are shown in Table 3.1. Of the 62 women enrolled in the study, 55 completed 2 or more samples, 7 completed one sample only (reasons: miscarriage, early delivery, moving out of the study area, unknown). Most of the women were highly educated (90% had some university education). We conducted 127 sampling sessions between October 2005 and August 2006, with the majority of the sampling in the winter and spring of 2005-06. Most of the women reported working (either part-time or full-time) and a small group, 10%, worked from home. For most (68%) participants, this was their first pregnancy; all other women had one child at home. Most (82%) of the women lived in the City of Vancouver; the rest lived in nearby districts.

A summary of the time spent in different micro-environments during the 48-hour sampling period is shown in Figure 3.1. The women spent on average, 22 hours/day (91 %) of their time indoors. Exposure to environmental tobacco smoke (ETS) was only reported during 14 sampling sessions (14 women). Mean exposure to ETS among those exposed was about 40 minutes/day (standard deviation = 30 minutes) with a maximum of 1.7 h/day. Average time spent exposed to cooking was 1.1 hours/day (SD=1.1) and cooking in a house with a gas stove, 0.83 hours/day (SD=0.72). Personal sampling results are shown in Table 3.2. Outdoor ambient air pollutant estimates from the land use regression model and interpolation of fixed-site monitors are shown in Table 3.3.

Table 3.4 and Table 3.5 list the subject, home, work and activity determinants that were associated with personal measured exposures in univariate analyses. We excluded education and ethnicity due to lack of variability. Time spent at home and work were highly correlated (Pearson's r=-0.85) so we considered only time spent at home. All home and work building size variables (area, volume, number of windows, number of rooms) were very similar so we selected the most significant predictor of the group for each pollutant. Environmental tobacco smoke exposure was not associated with any of the measured pollutant exposures.

Exposure Determinants Models

The exposure determinants that were significant in the final models for each pollutant are shown in Table 3.6. Because the personal measurements were log-transformed, we reported a percentage change in the personal measurement rather than the regression coefficients.

The final model for personal NO indicated that home gas stove increased exposures, time spent outdoors decreased exposure, and estimates of ambient outdoor pollution using *both* the traffic-based and monitor-based methods increased exposures. Because the outdoor estimates were not highly correlated and represented different components of outdoor pollution, we included both in the model where both were statistically significant predictors. The final NO model explained 62% of the total variability in the personal measurements (Table 3.7), although this was partially driven by a few outliers. Exclusion of the outliers reduced the variability explained to 56% with no change in effect estimates. The model for personal NO_2 exposures indicated that home gas stove presence and annual outdoor air pollution derived from the land use regression model both increased exposures, whereas increased home size, time spent at home both decreased personal exposures. Overall, the NO_2 model explained about 28% of the total variability (Table 3.7). In the absorbance model, increased measured levoglucosan and increased interpolated outdoor $PM_{2.5}$ both increased personal absorbance exposures. The final absorbance model explained 57% of the total variability. In the personal fine particulate ($PM_{2.2}$) model, the number of rooms decreased exposures, whereas time spent cooking in a house with a gas stove and outdoor interpolated $PM_{2.5}$ both increased personal exposures. The $PM_{2.2}$ model explained 29% of the variability in the personal measurements.

Of the many effects considered, gas stove in the home was the most consistently associated with increased personal measurements for all pollutants. Having a gas stove in the home predicted the largest increase in personal concentrations for NO (84% increase in homes with gas stove) and NO_2 (44%). Home gas stove alone explained about 58% of the variance between subjects in NO, about 10% for NO_2, little for absorbance and about 10% for fine particulate. The combination of outdoor air pollution from land-use regression models and the ambient fixed-site estimates explained 30% of the total variance in NO (58% of the between-subject variance). Outdoor annual land-use regression estimates (ambient monitor estimates were not significant) explained about 7% of the variance in NO_2 (10% of the between-subject variance); ambient fixed-site $PM_{2.5}$ (land-use regression estimates were not significant) explained only within subject variance in absorbance and PM, 27% and 17% of the total, respectively.

In results not shown[1], we compared the effects of outdoor ambient modeled estimates on personal exposures in adjusted (for any significant determinants, i.e. gas stove) and unadjusted (outdoor ambient as the only determinant) mixed effects models. For all pollutants except absorbance, the effect on personal measurements of a specified change in outdoor modeled exposures was not significantly different (1-4% in the effect estimate) between the adjusted and un-adjusted models. For absorbance, the change in personal measurements based on the outdoor ambient $PM_{2.5}$ estimate was 26% (unadjusted model), and 65% after adjusting for levoglucosan.

Discussion

This is the first study to measure personal exposures to NO and NO_2 gases for pregnant women and one of the few to measure particles. Many other studies have measured outdoor NO_2 at home as a marker for traffic-based pollutants, but direct measurement of this determinant is not feasible for large populations nor do home outdoor measurements perfectly reflect exposures. This is also the first evaluation of a land use regression (traffic-based) outdoor air pollution concentration estimate by personal monitoring, important given that these estimates are beginning to be used in epidemiological studies (23,24).

Personal samples of all pollutants showed greater variability than estimated outdoor pollution levels. This is consistent with our expectations and results from previous studies of personal exposure (25,26). Due to the influence of indoor sources and personal activities, personal measurements of exposure are often more variable than outdoor measures. In our case, we observed the greatest contrast in personal variability for NO likely because it is a primary pollutant released directly from traffic-based sources.

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[1] Results in Appendix E, Table E.35

Determinants of personal exposures

When comparing the exposure determinants that were important in this study to results of other studies, there are some important considerations. Firstly, are the exposure determinants particular to the population we studied, namely pregnant women? Secondly, are the determinants particular to the city, region and/or lifestyle? It is possible to compare our results to other studies in other locations, but difficult to determine the particularities of our specific population since there are very few personal monitoring studies conducted among pregnant women. We hypothesized that personal activities among pregnant women might differ as compared to the general population. Most personal monitoring studies have been conducted for populations of specific concern including children, the elderly, or patients with COPD or other diseases. Several authors have pointed out that differences in the activities between children and adults, or adults and COPD patients can lead to significant differences in personal exposures to air pollution (16,27).

Although limited activity pattern data make it difficult to determine the extent to which activities of pregnant women differ from women who are not pregnant, we compared our population to a randomly selected sample of 103 women (18-45 years) from Vancouver surveyed in 1996 as part of the Canadian Human Activity Patterns Survey (CHAPS) (28). We found significant differences (t-tests, $p<0.01$) between our study group and the CHAPS women for time spent at non-home locations indoors and time spent in a car or walking. Although, the women in our study spent only slightly more time at home (mean 67% vs. 64%), they also spent substantially less time in other indoor locations (6.5% vs. 10.3%), less time in cars (3.6% vs. 5.8%) and more time walking (2.7% vs. 0.6 %). Acknowledging the differences in data collection methods for this study compared to CHAPS, this suggests that our population of pregnant women only differs slightly from women in the general population.

Outdoor pollution estimates (using land-use regression and ambient monitoring data) as determinants

In all of our personal exposure models, except for NO_2, we found that outdoor monitor-based pollution concentrations were significant determinants of increased personal exposures. Outdoor interpolated concentrations alone explained about 30% of the total variance for NO and absorbance and 10% for $PM_{2.5}$. Land use regression estimates were significant only for NO_2 and NO. Other studies have shown that ambient pollution measurements (using regulatory air monitoring network sites) were related to personal exposure to varying degrees.

Few studies have measured personal NO or developed exposure models for NO concentrations.

There are mixed results from studies using ambient NO_2 to predict personal NO_2. Some have seen little relationship between personal and ambient (fixed-site) NO_2 measurements (29-31). Others were able to use ambient concentrations to predict personal NO_2 (32); however, it seems more common to find traffic-based indicators (density, distance to roads, degree of urbanization) that are moderately associated with personal NO_2 (29,33,34). Our results support this conclusion: that traffic-based metrics, in this case land use regression models, with high spatial and temporal variability are more commonly associated with personal NO or NO_2. On the other hand, fixed-site ambient (outdoor) measurements, with high temporal variability, are related to personal particle exposures, reflecting the lack of spatial variability in ambient particle concentrations and the importance of the indoor environment in modifying exposures.

The case of elemental carbon or absorbance is more varied. Several studies in Europe have found elemental carbon to be strongly associated with traffic metrics (26,34). In Europe, diesel particles are a large contributor to ambient elemental carbon (which is highly associated with absorbance). By contrast, in Seattle, Washington, (a very similar city to Vancouver in population and climate) a recent source apportionment study found that elemental carbon was a dominant feature of *both* mobile sources (diesel and gasoline) and vegetative burning, and that the elemental carbon strength in vegetative burning was highly seasonal (35). It is possible that the mixture of different sources contributing to elemental carbon concentrations in this area accounts for inability of traffic-based absorbance metrics alone to detect personal variability in exposures. We also found levoglucosan to be an important determinant of personal absorbance exposure, suggesting the importance of vegetative burning in our study.

In studies of fine particles, Gauvin et al. found that background PM_{10} concentrations explained 24% of the variance in personal $PM_{2.5}$ in children in France (25). Recently, a study in Spain among post-myocardial infarction patients found outdoor fixed-site ambient $PM_{2.5}$ and absorbance to be related to their respective personal measurements (36). These associations are driven by high temporal correlations between personal and fixed-site monitor based concentrations that have also been seen studies with numerous repeated measurements (>6) per subject over a limited period of time (16,26,37). In this study, we were able to detect within-subject associations for particles even with our relatively few repeated measures per person.

To understand the influence of outdoor pollution estimates on personal measurements in absence of information about other determinants, we developed regression models including only outdoor (land-use or monitor-based depending on the pollutant) estimates without adjusting for personal exposure determinants. Fixed effect values from these models were very similar to the adjusted models (with the exception of absorbance which was highly affected by levoglucosan measurements), indicating that the effect of ambient outdoor pollution on personal measurements was not affected by the presence of indoor sources and activities. This supports the use of ambient outdoor estimates as proxies for the influence of outdoor air pollution on personal exposure even in the absence of individual determinants data (i.e. Gas stove use).

Individual exposure determinants

Home gas stove (91% increase in exposure relative to no gas stove for NO) was highly significant in all models for all pollutants. Having a gas stove in the home has previously been shown to increase personal exposures (38,39); although this effect is not always detected for particles and gaseous pollutants, as in this study.

Time spent outdoors was shown to decrease exposure to personal NO. This is understandable because this metric included time spent in parks and other areas that have low levels of ambient pollution and high air movement. Alternately, it is possible that this simply reflects less time spent indoors and exposed to indoor sources of NO_x (e.g. gas stoves).

An increased number of rooms in the home decreased personal exposures, specifically for NO_2, absorbance and personal $PM_{2.5}$, possibly because larger homes may have increased air exchange rates and greater dilution of indoor sources. This is supported by results from other studies where increased home ventilation or air exchange rates significantly decreased personal $PM_{2.5}$ (16,40). Similarly, the use of air conditioning decreased exposures for $PM_{2.5}$ and absorbance likely by further increasing air exchange rates.

An unexpected result was that increased time spent indoors was associated with a slight decrease in personal NO_2 exposure. Previous work in Vancouver has shown that ambient traffic-based estimates of NO_2 show less spatial variation across the city than NO. With flatter concentration gradients across the city, perhaps being inside a home provides a stronger protective effect to reduce traffic-based NO_2 exposures.

We found that personal measurements of wood smoke tracers were important in personal absorbance models. This supports the findings from Maykut et al. (35) showing that, for the Pacific Northwest region, vegetative burning can be an important contributor to ambient elemental carbon. Cooking alone was important in univariate analyses with personal $PM_{2.2}$, but the only effect of cooking on personal $PM_{2.2}$ in multiple regression models was for homes with a gas stove. A few studies have also shown increased particle concentrations, especially ultrafine particles, from simply using a gas stove (41,42).

There are many determinants which were associated in univariate analyses but not in multiple regression models (Table 3.4 and Table 3.5). Wood fireplace presence was not associated with absorbance or PM as we might have expected, but no participants reported using wood to heat their homes. Most of the gas sources were associated with NO and NO_2 (heat, stove, fireplace) although they did not remain significant in multivariable models. None of the work variables were included in final models, likely because people spent the majority of their time at home. Although time spent in transit (motorized and non-motorized, as well as specifically in diesel buses) was tested, none of these measures were associated with personal exposures. Again, it is possible that relatively low ambient exposures in Vancouver mean that exposures specifically due to transit are not much greater than average ambient exposures over a 48-hour period. We collected information about windows use (open or closed) but this was only partially recorded by participants. Because of our low confidence in the reliability of this data, we excluded it from analysis.

ETS exposure was not important in predicting personal measurements for any pollutants. This is contrary to results of most studies but only a few women reported ETS exposure and none lived with smokers. Smoking is also prohibited by law in public spaces, workplaces and restaurants/bars in Vancouver. ETS exposure for participants in our study was reported only at bus stops, outdoor restaurants/patios or from smoker being outside a window at work.

Some limitations of this study are that we did not collect extensive repeats per subject and over all seasons. Having more repeated measures would increase our ability to detect the changes in activity and exposures over the course of pregnancy, and relate those changes to personal exposures. We were only able to characterize exposure over the course of a pregnancy to a limited extent since not all participants completed multiple measurements. However, this is one of the only studies to attempt repeated measures over pregnancy and the only study to do so for gaseous pollutants. We were also limited in our comparisons to $PM_{2.5}$ from other studies since we measured a slightly different cutpoint of fine particulate ($PM_{2.2}$). We did not collect data on use of incense or candles which have been previously shown as important particle sources in homes. Our samples were only collected on weekdays which may also bias our measurements towards a higher exposure due to the increased mobility of the population on weekdays (workdays). This is also a non-random sample of pregnant women with relatively high educational attainment. We don't believe this should affect ambient air pollution exposure or traffic exposure but it may be important for home characteristics and activity factors.

On the other hand, the study had several strengths. The low exposure to ETS in our population was important in allowing us to examine effect modifiers that may otherwise be hidden by this exposure. Also, by conducting this study in a city such as Vancouver with relatively low levels of ambient air contaminants, we can detect associations with home and work characteristics. We saw a large number of potential associations with personal exposures that may suggest further research directions.

Conclusions

This is one of the first studies to characterize personal determinants of exposures to environmental air pollution among pregnant women. We used a relatively novel traffic-based exposure estimate (using land-use regression), monitor-based measurements of ambient air pollution, personal characteristics and activities to develop models predicting personal measurements. Home gas stove was very important in predicting differences in personal exposures for all pollutants. However, despite the strong influence of gas stove presence in predicting increased exposure between subjects, traffic-based exposure estimates and ambient outdoor fixed-site estimates were important determinants of personal exposures, with the most marked effects for personal NO.

Figures and Tables

Figure 3.1 Average (Standard deviation) percentage of the 48-hour measurement period spent in different micro-environments during all sampling sessions. Second line is Range (Min-Max).

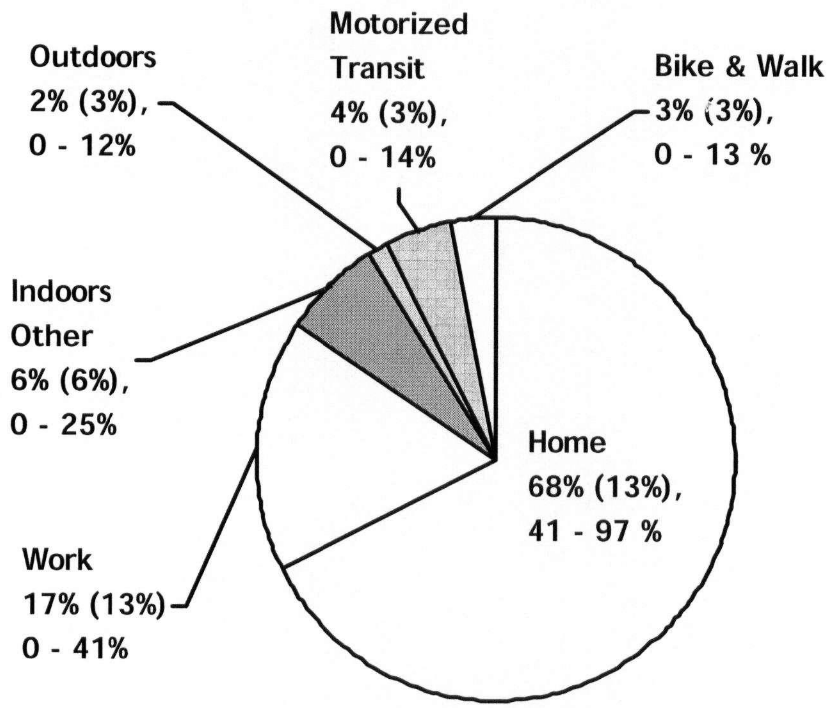

Table 3.1 Characteristics of the study population

Variables (n=62 women)	N	%
Annual household Income ($CAD)		
<40k / year	7	11
40-100k /year	32	52
>100k /year	23	37
Education		
Not specified	1	2
Trades or College	5	8
University	24	39
University, Graduate degree	32	52
Number of other children		
0	42	68
1	20	32
Home status		
Rent/Other	23	38
Own	38	62
Working Status		
Full time	39	63
time	16	26
Not working	7	11
Total sessions completed		
1	7	11
2	45	73
3	10	16
Season (n=127 sampling sessions)		
Heating	51	40
Non-heating	76	60
	Mean	**Range**
Age (years)	32 (4)	23-40

Table 3.2 Personal air pollutant exposures of 62 pregnant women in 1 to 3 48-hour sampling sessions (Total N=127)

Personal Measurements	N	Arithmetic Mean (Std Dev)	Geometric Mean (GSD)	Median	Range (Min-Max)	IQR[1]
NO (ppb)	127	48.5 (50.5)	36.71 (2.0)	34.2	6.9-473.5	37.5
NO_2 (ppb)	127	18.7 (9.2)	16.91 (1.6)	17.1	4.8-75.9	11.1
Absorbance (10^{-5} m^{-1})	120	0.9 (0.4)	0.82 (1.5)	0.8	0.2-2.4	0.5
$PM_{2.2}$ (ug/m^3)	124	11.3 (6.6)	10.02 (1.6)	9.7	4.2-45.3	5.74
Levoglucosan (ng/m^3)	124	15.2 (36.6)	5.39 (3.9)	6.1	0.8-329.6	11.1

[1] IQR= Interquartile Range (25^{th} -75^{th} percentile)

Table 3.3 Estimates of exposure of 62 pregnant women to outdoor ambient air pollutants during all 127 personal exposure sampling sessions. Estimates based on measurements from fixed-site monitoring stations and traffic-based models (land-use regression).

Outdoor ambient pollution estimates, N=127	Arithmetic Mean	(SD)	Geometric Mean	(GSD)	Median	Range (Max-Min)		IQR[1]
Land-use regression model[2]:								
NO (ppb)	28.1	(19.1)	23.16	(1.9)	22.7	6.4 -	150.6	24.5
NO_2 (ppb) (Annual)	17.4	(2.9)	17.10	(1.2)	17.3	8.3 -	26.7	2.48
Absorbance (10^{-5} m^{-1}) (Annual)	0.7	(0.3)	0.66	(1.8)	0.7	0.0 -	1.4	0.21
$PM_{2.5}$ (ug/m^3)	3.9	(1.3)	3.66	(1.6)	3.9	0.3 -	7.3	1.13
Fixed-site monitor interpolation[3]:								
NO (ppb)	20.9	(24.2)	13.98	(2.3)	13.0	1.9-	170.3	15.3
NO_2 (ppb)	20.2	(5.4)	19.47	(1.3)	20.3	8.8 -	36.3	7.07
$PM_{2.5}$ (ug/m^3)	5.3	(2.8)	4.63	(1.7)	4.6	1.5 -	15.0	3.14

[1] IQR= Interquartile range (25th-75th percentile).

[2] NO and $PM_{2.5}$ estimates were based on a monthly average, whereas NO_2 and absorbance used the annual average land use regression estimate. Results are shown for the land-use regression method (i.e. annual or monthly) that was most strongly associated with personal measurements.

[3] The monitor-based estimates used an inverse-distance weighted average of the hourly concentrations over the 48-hour sampling session from the nearest 3 monitors.

Table 3.4. Categorical variables related to personal exposures and initially offered in multiple regression models.

Categorical Variables		N	%	Initially offered in multiple regression models for[1]: NO	NO_2	ABS[2]	$PM_{2.2}$
Home characteristics (n=68 homes)							
Air Conditioner	No	65	96			x	x
	Yes	3	4				
Carpet Levels	0% Carpet	10	15	x	x		
	up to 25% Carpet	19	28				
	25-75% Carpet	19	28				
	> 75% Carpet	20	29				
Garage	No	45	66	x			
	Yes	23	34				
Gas Fireplace	No	53	78	x	x		
	Yes	15	22				
Gas Heating	No	40	59	x			
	Yes	28	41				
Gas Stove	No	40	59	x	x	x	x
	Yes	28	41				
Within 75 m of Major road	No	53	78				
	Yes	15	22				
Within 200 m of Highway	No	62	91		x		x
	Yes	6	9				
Windows	1-4 Windows	12	18	x			
	5-8 Windows, small	22	32				
	Many (>8) windows and/or glass wall	34	50				
Wood Fireplace	No	47	69	x			
	Yes	21	31				
Subject characteristics (n=62 women)							
Annual Household Income	<40k	14	11	x	x		x
	40-100k	66	52				
	>100k	47	37				
Work characteristics (n=49 workplaces)							
Garage Y/N	No	30	61	x	x		
	Yes	19	39				
Particle Source	No	44	90		x		
	Yes	5	10				
Ventilation Type	Natural Ventilation	13	27	x	x		
	System Ventilation	36	73				
Windows Classification	No Windows	5	10		x		
	1-4 Windows	24	49				
	5-8 Windows, small	8	16				
	LOTS of windows, glass wall	12	24				

[1] 'x' indicates that the variable was associated with this personal measurement (pollutant) in univariate analyses and considered for inclusion in multiple regression models.
[2] ABS=Absorbance

Table 3.5 Continuous variables related to personal exposures and were initially offered in multiple regression models.

Continuous variables					Initially offered in multiple regression models for[1]:			
	Mean	(SD)	N	Range (min-max)	NO	NO_2	ABS	$PM_{2.2}$
Home building age					x			
Home number rooms	6.7	(3)	68	3 - 16		x	x	x
Subject age	32.0	(4)	62	23 - 40			x	
Work building age (years)	34	(23)	49	1 - 100	x	x		
Work area (m^2)	256	(863)	49	0 - 5574	x			
Work volume[2]	1290	(5111)	49	0 - 34000			x	x
Time at/near home (h/day)	16.3	(3.2)	127	10 - 23.3		x	x	
Time outdoors[3] (h/day)	0.25	(0.55)	127	0 - 2.8	x	x		x
Time cooking (h/day)	1.1	(1.1)	127	0 - 7.1	x			x
Time cooking in house with gas stove (h/day)	0.8	(0.7)	127	0 - 3.3			x	

[1] 'x' indicates that this variable was associated at $p<0.1$ in univariate analyses and was considered in multiple regression models.
[2] Work volume was log-transformed.
[3] Time spent outdoors, not including biking and walking.

Table 3.6. Percentage change (95 % confidence interval) in personal measurements for exposure determinants that were significant in multiple regression mixed models.

Variable influencing exposure	Change in variable[1]	Resulting percent change (95% confidence interval) in personal measured pollutant[2]			
		NO (%)	NO_2 (%)	ABS (%)	$PM_{2.2}$ (%)
Home Gas Stove	Yes (vs. no)	89 (58, 127)	44 (21, 70)	20 (5, 37)	35 (6, 70)
Home # of Rooms	Increase of 1 room	--	-4 (-6, -1)	-3 (-5, -1)	-5 (-8, -2)
Home Air Conditioning	Yes (vs. no)	--	--	-41 (-59, -17)	-42 (-64, -7)
Outdoors	Increase of 1 hr/day	-8 (-15, 1)	--	--	--
At/near Home	Increase of 1 hr/day	--	-3 (-5, -1)	--	--
Cooking with Gas Stove	Increase of 1 hr/day	--	--	--	8 (0, 16)
Wood smoke tracer[3]	Log_{10} increase of 1 ng/m^3	--	--	38 (26, 50)	--
Traffic-based outdoor air pollution	NO=25 ppb, NO_2=2.5 ppb	28 (14, 44)	11 (4, 19)	--	--
Monitor-based outdoor air pollution	NO=15 ppb, $PM_{2.5}$=3.1 ug/m^3	19 (12, 26)	--	28 (21, 35)	21 (12, 31)
Intercept		18.0 ppb	14.7 ppb	0.7 (m^{-1} 10^{-5})	8.5 ug/m^3

[1] Reported change in exposure determinant chosen for ease of interpretation (i.e. 1 h/day or 1 room) for all home and activity variables, or using interquartile ranges for outdoor pollution levels.
[2] -- Variable not significant in the final model for that pollutant.
[3] 'Wood smoke' refers to the levoglucosan concentration measured in personal samples.

Table 3.7 Between- and within-subject variance components of the random effects only models (baseline[13]) and the final mixed-effect models (as outlined in Table 3.6), and the proportion of variance in personal exposures explained by the fixed effects in the models[1]

Model description	Variance component (95% confidence limits)		% Variance explained (compared to baseline)		
	within subject (σ_{WS})	between subject (σ_{BS})	σ_{WS}	σ_{BS}	Total
NO (dependent)					
Baseline[2]	0.33 (0.24 ,0.48)	0.19 (0.10 ,0.47)	.	.	.
Final model	0.15 (0.11 ,0.21)	0.05 (0.02 ,0.20)	56	72	62
NO_2 (dependent)					
Baseline	0.09 (0.06 ,0.13)	0.11 (0.07 ,0.20)	.	.	.
Final model	0.08 (0.06 ,0.11)	0.06 (0.04 ,0.14)	9	42	28
ABS (dependent)					
Baseline	0.17 (0.12 ,0.25)	0.02 (0.01 ,1.34)	.	.	.
Final model	0.05 (0.04 ,0.08)	0.03 (0.01 ,0.08)	68	-15	57
$PM_{2.2}$ (dependent)					
Baseline	0.17 (0.12 ,0.25)	0.06 (0.03 ,0.25)	.	.	.
Final model	0.13 (0.09 ,0.19)	0.03 (0.01 ,0.24)	24	43	29

[1] Personal measurements were log-transformed.

[2] Baseline model contained subject as a random effect and no fixed effects. Final model contained subject as a random effect and fixed effects from Table 3.6.

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Chapter 4 Location-based time-activity patterns of pregnant women: Changes over pregnancy[1]

Introduction

Pregnant women are increasingly considered a special population of interest in assessments of environmental contaminants due to evidence that a women's exposure to contaminants can lead to adverse effects on the fetus (1). For example, there is evidence of links between adverse birth outcomes and exposure to outdoor air pollution (2), indoor air pollution (3) and pesticides (4). Exposure to contaminants is often evaluated through the use of location-based activity pattern data to establish when and where people spend their time. Activity data can be combined with measured or estimated contaminant concentrations to assess exposures in different microenvironments for use in epidemiological studies or risk assessments. Characterizing the activities of women during pregnancy is an important contribution to understanding the association of environmental exposures and adverse birth outcomes.

Two large scale activity pattern surveys in the US (National Human Activity Patterns Survey, NHAPS) and Canada (Canadian Human Activity Patterns Survey, CHAPS) were designed to provide data for use in exposure assessment modeling (5). Both studies collected highly detailed 24-hour time-activity diaries from participants (selected randomly in targeted cities) using Computer Aided Telephone Interviewing (CATI) techniques. Results of these surveys have been used to estimate percentages of the population that may be highly exposed to specific contaminants. For example, a recent model was developed to predict particulate exposure ($PM_{2.5}$) for 11 age-gender population subgroups in Toronto, Canada using CHAPS data (6). Similarly a study in 2005 used (7) NHAPS data to determine the probability and distributions of exposures in the U.S. population to contaminants that enter the home via the water supply.

[1] A version of this chapter will be submitted for publication.

Information on the location-based activity and mobility patterns of women during pregnancy is sparse in the literature. CHAPS did evaluate pregnancy status of subjects, but only 22 of the 2301 respondents to the entire survey were pregnant (8). NHAPS, a much larger survey, did not collect information regarding pregnancy status. Several studies have evaluated physical activities of women during pregnancy, but these were focused on exercise levels during pregnancy (9,10) and on physical weight relative to activity patterns (11) rather than exposure to contaminants. A recent review discussed the relationship between physical activity and psychological mood among pregnant women (12). No previous studies have focused simply on changes in specific areas and locations that dominate women's time during pregnancy.

As part of a study measuring personal exposure to traffic-related outdoor air pollution (Chapter 2), we collected time-activity data for 62 pregnant women, up to 3 times during the pregnancy. In the current study, we aimed to answer the following questions: (1) do activity patterns of pregnant women differ from women in the Canadian population, (2) do the activities of pregnant women change over pregnancy.

Methods

Study Design

The study population consisted of 62 pregnant women living in the metropolitan area of Vancouver, Canada in 2005-2006. Women were recruited through word of mouth, at prenatal yoga, fitness or prenatal classes and through posters at community centers. The study protocol and material was approved by the University of British Columbia Behavioural Research Ethics Board (approval #B05-0441). Subjects were limited to non-smokers living with non-smokers and experiencing low-risk pregnancies. The women carried air pollution monitoring equipment during the sampling sessions (Chapter 3, to be submitted). They were asked to complete two or three 48-hour sampling sessions, on weekdays only, spaced evenly across trimesters of pregnancy. We had difficulty recruiting women in their first trimester, possibly because many women wait until late in the first trimester to publicly acknowledge their pregnancy, so most were in their second trimester and completed two sessions.

At the first session, we administered a basic questionnaire to document age, work status, education, annual family income, due date, ethnicity, and home rentals/ownership. Gestational age (weeks of pregnancy) was calculated from the self-reported due date. During each session, the women recorded their activities at 30 minute intervals in a 48-hour activity log. After giving birth, each subject was interviewed over the phone or in person. We presented a thank-you gift (baby clothing item) and administered a brief questionnaire on self-reported birth weight/length, pregnancy or birth complications. Since the focus of the study was on exposure measurements, the post-birth survey was used simply for descriptive purposes.

Measurement Data

At the first visit, the technician explained how to complete the time-activity log and provided written instructions. A sample of a line from a completed activity log is shown in Figure 4.1. The time-activity log was a self-administered form (4 pages) on which the women circled their activities and locations during every ½ -hour period. The activities and locations on the time-activity log included:

- current location (indoor at home, work, other or outdoor)
- transit activity (time of transit and method: car, bus and bus type (diesel, electric or "Skytrain" elevated electric rail), walk, other); if "other" was indicated, participants always noted bicycling in the notes column and subsequently coded as "bike".
- whether they are currently nearby to cooking, smoking or open windows
- current level of activity (high, medium, low); low is "at rest" (sleeping/rest); high is the highest level of physical activity they do

Omitted from the figure is a "notes" column where participants could indicate any specific information about their activities during that half-hour segment. Participants were asked to indicate no more than 2 activities or locations during a ½ hour period. When more than one activity was specified during a half-hour period, we assigned both activities to a time of 15 minutes each. After every 48-hour sampling period, we collected the activity log from the participants.

For each activity log, we calculated the total minutes for each activity. Each event was divided by the total minutes in the activity log to determine the percentage of the sampling time that each activity represented. We attempted to ensure that all sampling sessions were as close as possible to 48 hours (2880 minutes). All percentages were multiplied by 24-hours and results are classified in hours/day.

Comparison Group

For a comparison population of mostly non-pregnant women (4/99 women pregnant), we obtained data on activity patterns from the Canadian Human Activity Patterns Survey (CHAPS) (8) from Health Canada. This survey was conducted in 1994-95 on 2381 respondents in Toronto, Vancouver, Edmonton and Saint John, NB. The survey consisted of a 24-hour recall diary and computer-aided telephone interview of randomly selected individuals in these four cities.

We limited the CHAPS data to women, ages 17-45, weekday samples only, in Vancouver because there were some differences in time-activity data between cities. The CHAPS data had more specific location information than the pregnancy cohort (our study population) so we collapsed the CHAPS locations for comparison purposes. The more detailed CHAPS locations in the home (e.g. home bedroom, kitchen), outdoors (e.g. park, parking lot, street), transit (bike, car, truck, bus) were collapsed to the categories used in the pregnancy cohort. We extracted time at work from the activity portion of the CHAPS dataset and then subtracted it from time in non-home locations (assuming work was not at home) or from time at home (if subject had no time in non-home locations, assuming work from home). We verified the re-categorization of the CHAPS data by making sure each subjects' time added up to 24 hours. Educational attainment was also recoded to parallel our study of pregnant women and work status (worker or non-worker) was generated from the time spent at work variable.

Data Analysis

All analysis was conducted in SAS (v9.1 SAS Institute Inc., Cary NC). We generated frequency distributions to investigate the shape of the distributions for all activity variables in our study. Highly skewed variables were log-transformed for analysis. We compared the demographic and activity variables available from our study (pregnancy cohort) and the CHAPS dataset. The mean activity and continuous demographic variables were compared using student's t-tests.

A priori, we considered all the questionnaire variables as potential predictors of activity: annual household income, education, work status, other children, last trimester of pregnancy, rent/own home, season, ethnicity, weeks of pregnancy, and work category. Work category (13 categories: e.g. education, engineering/science, recreation, food/restaurant, healthcare, research) was excluded because of small numbers of subjects per category. The remaining variables were assessed in univariate analysis of variance with activity data. Because we were interested in changes in activity over pregnancy, we only considered activity variables that showed significant differences ($p<0.1$) by trimester and/or weeks of pregnancy. After identifying activity variables of interest, we assessed the association between activity data (dependent) and season and trimester (independent variables) because activity changes can be strongly modified by seasonal effects. Only activities that did not vary according to season were analyzed in multiple mixed-effects regression models to predict activity as the dependent variable. We used a mixed effect structure with individual factors (work status, parity, weeks of pregnancy) as fixed effects and subject as a random effect to control for within subject correlations and repeated measurements on each person. A backwards stepwise regression was used to eliminate variables until all remaining variables had p-values <0.05. We used this p-value to retain as many potentially predictive variables as possible.

After identifying activity variables that were modified by weeks of pregnancy, independent of season, we modeled the trajectory of change in the proportion of time spent at home by trimester of pregnancy for the whole cohort using a SAS extension developed by Jones et al. (PROC TRAJ) (13). This is a group-based modeling approach that identifies groups with distinct trajectories, estimates the proportion of the population in each group and assigns group memberships to the individuals. We used this method to model the change in time at home across trimester of pregnancy and to identify groups in the data based on similarities in the patterns of change. To identify the optimal number of groups, we followed methods described by Xie et al. (14). We started with a two-group model and refitted the model until a 5 group model was fit. For each model, we first fit the highest order of polynomials possible (cubic, highest possible order in Proc TRAJ). The model was then refit with lower-order polynomials if the highest order polynomials were not significant. The Bayesian Information Criterion (a model fit criteria) was recorded for each final model and used for model selection among models with differing numbers of groups (2-5 groups).

Results

Descriptive results from the questionnaire variables (n=129, 62 women) and from the CHAPS comparison group (n=103, 103 women) for which we have parallel data are shown in Figure 4.2. The two groups had similar age distributions and similar proportions of nulliparous women. The women in our study population were more highly educated, more likely to work (full or part-time). Because our study recruitment was mostly in the fall-winter of 2005-2006, data was not collected evenly across all seasons.

Time spent at work was normally distributed (with a secondary mode at zero) and all time-activity measurements were positively skewed. Descriptive activity results from this pregnancy cohort and the CHAPS comparison group are shown in Figure 4.2. The pregnant women in our study spent significantly less time indoors in "other locations other than home or work", less time in cars or buses and more time walking than the CHAPS women. Detailed results and confidence intervals for our study of pregnant women and the CHAPS activity patterns are shown in Table 4.2.

The activity measures for physical activity levels were interpreted differently among subjects. Although we attempted to clarify the meaning of the question, some subjects coded only sleeping as "low" whereas others coded most daily activities as "low". Because of the difficulty in interpreting the results and low confidence in the metric, we did not further analyze these responses.

Mean and 95% confidence intervals for all activity measures stratified by trimester of pregnancy are shown in Table 4.3. Statistically significant differences were noted for time spent at/near home (higher in last trimester), time spent at work (higher in first trimester) and time spent outdoors (highest in last trimester). Further stratification by season of measurement showed no seasonal trends in time spent at home or work. However, we did see a significant trend of increased time spent outdoors in the summer (Mean (SD): Summer=2.2%, Winter=0.3%, $p<0.0001$). Because recruitment was concentrated in the fall/winter, the majority of women delivered in the summer and spring leading us to suspect that the increased time spent outdoors in the last trimester may be confounded by season. In a model regressing season and weeks of pregnancy on time spent outdoors (dependent), we confirmed that season was the only significant predictor of time spent outdoors.

Frequency distributions of time-activity data from our study revealed a distinctly bimodal distribution for time spent at home, with modes at 14 and 19 hours/day. Multiple regression models focussed on time spent at/near home alone since this was not confounded by seasonal effects. Mean time at home by trimester, income, parity and work status, variables which were significantly associated ($p<0.05$, Anova) with time at home, are shown in Table 4.4. Education, age and season did not predict the amount of time spent at home.

Weeks of pregnancy alone predicted time at home with and without adjusting for other significant predictors (income, parity and work status) (Models 1 and 2 in Table 4.5). Both models include a random effect for subject. A 1-week change in the stage of pregnancy predicted a 5 minute increase in time spent at home; over a trimester, about 1 hour increase (4 %) in time at home. Having no other children predicted a decrease in time spent at home (-1.5 hrs/day), lower income (2.6 hrs/day, lowest income category) and being a non-worker both increased time at home (3.5 hrs/day). The final adjusted model explained about 44% of the between subject variance in time spent at home and 29% of the total variance. Weeks of pregnancy alone explained 12% of the within subject variance regardless of adjustment for other factors.

Trajectory modeling (Figure 4.3) showed significant trends of increased time at home by trimester of pregnancy. The highest BIC score was for a two-group model with linear parameters (polynomial order=1). One group represented about 62% of the study subjects who spent about 14 hours/day at home during the first trimester. The second group was about 38% of the study population and contained those who spent more time at home, about 16 hours/day during the first trimester. The slope from the predicted model for both groups was significant and showed a slightly stronger increase in the second group (slope group 1=0.8 hours/trimester; group 2 =1.3 hours/trimester). Post-hoc examination of the groups (using cross-tabs) identified by the trajectory modeling indicated that the first group (lower intercept) was only workers and tended to include women with higher household income. The second group (more time at home at baseline) was a mix of workers and non-workers and lower to middle household income.

Discussion

In this study, we collected activity-location information using a repeated time-activity survey among pregnant women. The survey was simple to implement and required little effort for the subjects. There were some significant differences (time in motorized transit, time walking) between the pregnant women and non-pregnant women from the CHAPS reference population. Increased weeks of pregnancy predicted an increase in time spent at home in the cohort; no other activity patterns were predicted by stage of pregnancy. Parity, income and work status also predicted time at home. Trajectory models identified two distinct groups in the cohort, those who were always workers, and those who didn't work or worked part-time.

To our knowledge this is the first manuscript describing location-based activity patterns of women during pregnancy. Population-based studies have excluded pregnant women either because pregnancy is already a risk factor for the health effect being studied (15) or because it was difficult to address exposure for this specific sub-population (16). Exposure measurement is of particular importance during pregnancy because of the potentially teratogenic effects of some exposures (e.g. mercury, environmental tobacco smoke or ionizing radiation) or their influence on other aspects of fetal growth or well being (e.g. effects of air pollution on intrauterine growth retardation (17), brain function impairment in children(18)).

We compared the pregnant women in our study to a comparison group from the 1994-95 Canadian Human Activity Patterns Survey. Although we used a similar age range, city and sampling day (weekdays only), there were some differences in data collection, sampling methods and subject population between our study and the comparison group. While the CHAPS data is a random sample, our population may not be representative. Non-random sampling may have introduced specific demographic or socio-economic factors into the cohort which are peculiar to this specific population of pregnant women. Decreased time in cars and increased time walking could be because the women were pregnant, but may be confounded by the non-random sample. Most of our subjects lived in dense urban areas, were health-conscious (attended prenatal yoga or athletics) and many were students or worked on the university campus. However, others have also found that time spent walking increased during pregnancy (specifically in the last trimester) while all other physical activities decreased (9,19). The CHAPS survey also used a detailed CATI phone interview to elicit data for the previous 24 hours and we used a short self-reported 48-hour log. These differences in sampling methodologies may have introduced a systematic bias when the variables were recoded. For example, we found that pregnant women were more likely to spend time indoors than comparable non pregnant women. However, the differences we observed in time spent indoors (locations other than home/work) could be explained by differences in data coding; our study coded only 3 locations (home, work, other), whereas we calculated these 3 locations by collapsing various fields in the CHAPS data.

We showed results indicating an increase in time spent at home over the course of pregnancy. We were able to detect this change over pregnancy using a relatively simple, non-invasive tool to measure time-activity patterns (specific to location) among this population. These results have not been demonstrated elsewhere although some have shown increased time in domestic or sedentary activities during pregnancy. A cross-sectional study found an increase in energy expenditure from household/caregiving activities for pregnant women in the last trimester of pregnancy (19). We also found that increasing income, being nulliparous and a worker was associated with a decreased time spent at home. Several others have reported the same factors as being associated with increased physical activity among pregnant women (19-21) which suggests an inverse relationship between our measure of time spent at home and physical activity measures in other studies. These were all cross-sectional studies using various methods: self-reported activities based on an interview at time of birth, 24-hour recall diaries during each trimester and a random sample of the population from a behavioural risk factors surveillance system.

The specific increase we noted, about 1 hour/day more time at home per trimester, could be significant when assessing exposure in other studies. For example, if there was environmental tobacco present in the home, an increase of 2 hours in time spent at home from the 1st to 3rd trimester could be a substantial change in the woman's exposure. Most adults spent between 14-19 hours/day (60-80%) of their time at home, so 2 hours more time at home could increase exposure by 10-15% over the course of pregnancy.

The trajectory analysis identified two clear groups differentiated by time spent at home although both showed an increase in time spent at home during the latter stages of pregnancy. In other studies (NHAPS) of time spent at home (5) differences were at least partially explained by working vs. non-working (outside the home) status. That workers and non-workers represent slightly different groups is unsurprising, but nevertheless interesting when developing exposure assessment models that encompass the entire population. Based on these results, pregnant women who are non-workers could have increased exposures in the home or near to home than workers.

Consideration of "sensitive windows" of exposure for women during pregnancy has been recommended for evaluating health effects on the fetus (1). For example, early gestational age is important for central nervous system malformation and congenital malformation, whereas later gestation is important for lowered growth. The implications of an increased time spent at home with trimester of pregnancy are important for exposure assessments based on residential address or assessments of the home microenvironment. Secondly, when examining exposures in the home it would be important to consider the implications of increased exposure later in pregnancy due to increased time spent at home. Accurate methods of exposure measurement in pregnancy which take into account activity patterns will be critical for linking putative exposures with relevant pregnancy outcomes.

Although these results are the first systematic evaluation of changing exposure-relevant activity patterns during the course of pregnancy, they should be viewed as primarily as investigative or hypothesis generating. Our study was also limited in the consideration of activity variables which were confounded by season because of the 80% of the delivery dates in our study population clustered around the spring and summer. Study participants were self selected and were highly educated, health-conscious and lived mostly in urban (rather than sub-urban) areas compared to the general sample of women in the CHAPS study, who were sampled by random-digit dialling. Our sampling occurred on weekdays only, so the results are specific to the work week.

Conclusions

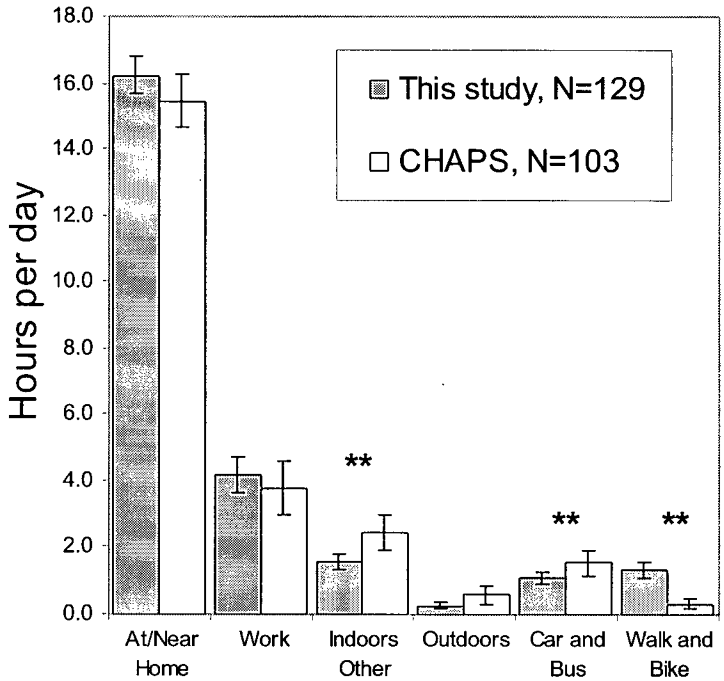
We demonstrated the use of a simple tool to detect changes in location-activity patterns among pregnant women during the course of pregnancy. Our results suggest a natural increase in time spent in home locations with increasing weeks of pregnancy. The trend was independent of other factors that decreased time spent at home including higher family income, having other children and having full or part-time employment.

Figures and Tables

Figure 4.1 Sample of the activity log

Time	Indoors			Outdoors		Transit						Activity Level	Cooking		Tobacco Smoke		Windows Open		Wearing Sampler	
	Home	*Work*	*Other*	*Near Home*	*Away*	*Car*	*Bus*	*Bus Type**	*Walk*	*Other*	*mins*	*Lo Mid Hi*	*Y*	*N*	*Y*	*N*	*Y*	*N*	*Y*	*N*
8-8:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y	N	Y	N	Y	N	Y	N

Figure 4.2 Mean time and 95% CI (error bars) by location[1]



[1] Activities showing significant differences (by t-tests) are indicated with "**" in the graph.

Figure 4.3 Trajectory model for time spent at home by trimester of pregnancy

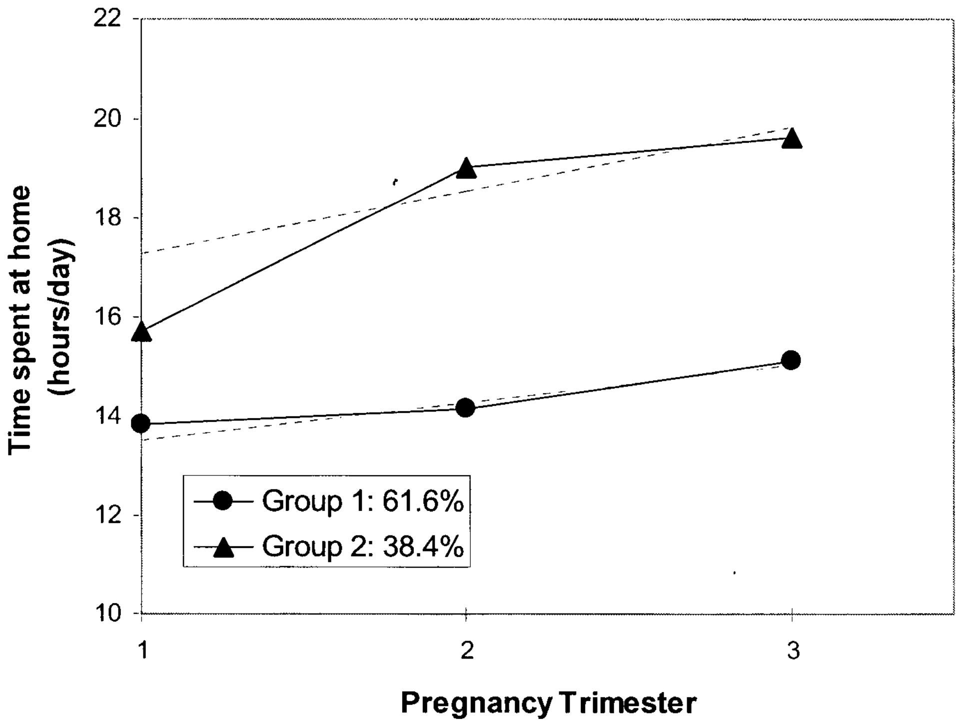


Table 4.1 Descriptive results (frequencies and means) for this study and the Vancouver subgroup of the CHAPS study.

Variable	Level	Pregnancy cohort (n=129)	CHAPS Vancouver only (n=103)
Is Pregnant? Y/N	No	0	99 (96%)
	Yes	129 (100%)	4 (4%)
Education Level	Not specified	2 (2%)	0
	High School	0	44 (43%)
	Trades or College	7 (5%)	19 (18%)
	University	51 (40%)	27 (26%)
	University >Masters	69 (53%)	13 (13%)
Number of Other Children	None	85 (66%)	67 (65%)
	1	44 (34%)	14 (14%)
	2	0	15 (15%)
	3 or more	0	7 (7%)
Works outside the home? Y/N	No	12 (9%)	27 (26%)
	Yes	117 (91%)	76 (74%)
Worked on Sample Day? Y/N	No	32 (25%)	54 (52%)
	Yes	97 (75%)	49 (48%)
Season	Winter	40 (31%)	35 (34%)
	Spring	50 (39%)	33 (32%)
	Summer	21 (16%)	28 (27%)
	Fall	18 (14%)	7 (7%)
Subject Age (mean and 95% CI)		32 (32 , 33)	31 (30 , 33)

Table 4.2 Mean hours per day (95% CI) in various activities for this study and comparison groups[1]

	Mean hours/day (95% CI)[2]					
Activity/Location Variable	**Pregnancy cohort (129 samples, 62 women)**			**CHAPS (103 women)**		
At/Near Home	16.2	(15.7,	16.8)	15.5	(14.7,	16.3)
Work	4.2	(3.6,	4.7)	3.8	(3.0,	4.6)
Indoors Other	1.6	(1.3,	1.8)	**2.5**	**(1.9,**	**3.0)**
Outdoors	0.3	(0.2,	0.4)	**0.6**	**(0.3,**	**0.8)**
Car	0.9	(0.7,	1.0)	**1.4**	**(1.1,**	**1.7)**
Bus	0.2	(0.2,	0.3)	0.1	(0.1,	0.2)
Walk	**0.7**	**(0.5,**	**0.8)**	0.2	(0.1,	0.2)
Bike	0.1	(0.0,	0.1)	0.0	(0.0,	0.1)

1 Bold numbers indicates significant differences using Student's t-tests (p<0.1)

2 Bold numbers are higher means when differences between two study groups are significant.

Table 4.3 Mean hours per day (95% CI) in specific activities/locations by trimester of pregnancy (this study)

	Mean hours/day (95% CI)		
Activity/Location	**1st Trimester**	**2nd Trimester**	**3rd Trimester**
	n=11	**n=62**	**n=54**
At/Near Home	14.4 (13.29 - 15.42)	16.1 (15.3 - 17.0)	**16.9 (16.0 - 17.8)**
Work	**5.57 (4.44 - 6.70)**	4.26 (3.46 - 5.06)	3.67 (2.76 - 4.58)
Indoors Other	2.24 (0.90 - 3.57)	1.56 (1.25 - 1.87)	1.39 (1.05 - 1.74)
Outdoors	0.00 (0.00 - 0.00)	0.15 (0.07 - 0.24)	**0.42 (0.22 - 0.62)**
Car	1.11 (0.51 - 1.70)	0.87 (0.67 - 1.07)	0.81 (0.60 - 1.01)
Bus	0.27 (0.01 - 0.54)	0.24 (0.14 - 0.35)	0.18 (0.08 - 0.27)
Walk	0.44 (0.19 - 0.69)	0.74 (0.58 - 0.91)	0.60 (0.42 - 0.77)
Bike	0.02 (0.00- 0.07)	0.06 (0.00 - 0.13)	0.06 (0.00 - 0.13)

Table 4.4 Mean time spent at home stratified by individual categorical factors

Variable	Anova, p-value	Values (mean, min-max)[1]	N	Time spent at home (hours/day) Mean	(SD)
Income	0.0002	40,000	14	17.9	(3.3)
		40,000-100,000	66	17.0	(3.0)
		100,000 + *	47	14.8	(2.9)
Other children	0.0030	No	84	15.7	(3.1)
		Yes	43	17.4	(3.2)
Trimester	0.0478	1 (11 weeks, 7-14) *	11	14.4	(1.6)
		2 (22 weeks, 15-28)	62	16.1	(3.3)
		3 (33 weeks, 29-36) *	54	16.9	(3.2)
Worker[2]	<.0001	No	12	20.4	(1.3)
		Yes	15	15.9	(3.0)
At work on sampling day	<.0001	No	32	20.0	(1.5)
		Yes	95	15.0	(2.5)

1 Groups which are significantly (α=0.05) different (using paired t-test for groups) identified by *
2 Most "Workers" were at work on sampling days. Little difference in means for "At work on sampling day" as opposed to "Worker".

Table 4.5 Effect estimates for models predicting percentage of time spent at/near home (dependent)

	Mean Intercept[1]	Effect Estimate ($CL_{5\%}$, $CL_{95\%}$) Predicted change in hours/day for effect	p-value[2]
Model 1 (Weeks Only)	14.3 (12.7 , 15.9)		
Weeks of Pregnancy		0.1 (0.0 , 0.1)	0.0065
Model 2 (Final Model)	13.7 (11.9 ,15.5)		
Income: <40k		2.60 (0.6 ,4.6)	0.0131
Income: 40-100k		1.92 (0.6 ,3.2)	0.0043
Income: >100k		Reference	
Non-Worker		3.47 (1.4 ,5.5)	0.0013
Other children=No		-1.48 (-2.8 ,-0.1)	0.0313
Weeks of Pregnancy		0.08 (0.0 ,0.1)	0.0067

1 All models included subject as a random effect (random intercept) to control for within subject correlation, so the mean intercept is the population mean of all individual (subject-specific) intercepts.
2 P-value from mixed effect regression model fixed effect estimate.

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Chapter 5 General Discussion

Exposure assessment of traffic-based air pollution for population health studies has been characterized by a wide range of different methods and models (1). Traditionally, most studies used central monitors to estimate exposures: an approach that captures temporal variability but may not reflect spatial variability in concentrations. New approaches have used land-use regression models that reflect small-scale spatial differences in air pollution (2,3) but are generally used for chronic exposure studies. Using exposure models that capture high resolution spatial variability has resulted in higher (and more precise) associations with health effects when compared to methods that do not consider spatial variability in concentrations (4,5). No previous studies have evaluated these relatively novel models that aim to capture small-scale variability in exposures. Similarly, the impact of individual mobility on exposure estimates has been discussed in the literature but rarely evaluated (6). In this thesis, personal exposure measurements were collected and used to evaluate modeling approaches using central monitors and a land-use regression model (7). Impacts of individual mobility were also evaluated in this thesis by combining individual mobility information with the land-use regression model and comparing the enhanced model (including mobility) to personal measurements.

This thesis is the first evaluation of land-use regression modeling for traffic-based air pollution using personal measurements. This is an important contribution to exposure assessment methods used in epidemiological studies. The research in this thesis was unique in its focus on evaluating both ambient monitoring *and* land-use regression: methods with different spatial and temporal characteristics. By using repeated measures and mixed effects regression techniques, the ability of exposure estimation methods to predict personal exposures could be evaluated with respect to their ability to capture spatial and temporal variability.

Various exposure assessment models and methods have been used in studies of air pollution and birth outcomes. In assessing exposure for pregnant women, most studies have modeled exposures using ambient monitors, while others used traffic metrics. Results across studies with various designs and using different methods to assess exposure have shown increasing evidence of associations between air pollution and adverse birth outcomes (8). Because the period of pregnancy is intermediate in length (i.e. not necessarily a chronic exposure), exposure assessment for this population requires approaches that address seasonal changes in pollutant concentrations while also considering spatial variability. Few studies have collected measurement data for this population and none have compared measured to modeled exposures specifically for pregnant women. A second unique aspect was the focus on understanding factors that influence exposure to air pollution and activities among pregnant women. Given increasing concern about in-utero exposure to contaminants (9), the novel exposure and activity measurements collected in this thesis have increased our understanding of the determinants of exposure and activities among this population.

Key findings

Evaluation of Air Pollution Exposure Models

Personal monitoring samples (NO, NO_2, absorbance and $PM_{2.5}$) from 62 pregnant women, repeated across pregnancy, were compared to modeled exposures at home using land-use regression and interpolation of ambient monitoring data. Only NO was associated in all analyses with both modeling approaches (NO: Pearson's r=0.49 for land-use regression at home; r=0.54 for ambient monitor inverse distance weighted estimates) and this pollutant showed the strongest associations with personal measurements compared to other pollutants (r=0.29 to -0.10 (most non-significant)). The variance in personal measurements explained by the ambient monitor-based models was mostly due to temporal correlations between modeled and measured exposures. This is shown by the within subject variance (σ_{WS}) component (due to temporal variability) which was the dominant component of the total variance explained by ambient methods (NO: σ_{WS} explained 37% of the total variance in personal samples; σ_{BS}= 14%; Absorbance and $PM_{2.5}$: σ_{WS} explained 9-11% of the total variance in personal samples; σ_{BS}= <0%). Incorporating work locations in the NO land-use regression model explained more between subject (primarily spatial) variability (σ_{BS}) than home alone (NO land-use regression at home: σ_{BS}= 4%; using home and work: σ_{BS}= 20%). When including only samples where subjects spent the majority (>65%) of their time at home, land-use regression estimates (NO: r=0.72) were more strongly correlated with personal measurements than were estimates based on ambient (inverse-distance weighting) measurements (r=0.59). In situations where a subjects' mobility is known (mostly at home) or accounted for (i.e. by including work location), land-use regression appears to perform as well or better than ambient methods at predicting personal exposures.

Results from **Chapter 2** indicate that land-use regression models show promise for capturing variability between subjects; however, only for highly spatially variable primary pollutants (such as NO). The more distinct spatial variations in the NO land-use regression surfaces compared to other pollutants likely contribute to the increased ability of this surface to capture spatial variability between subjects. In general, $PM_{2.5}$ is less spatially variable than primary pollutants such as NO at the intra-urban scale because it is affected by sources other than traffic and has a longer atmospheric lifetime. So, it is unsurprising that land-use regression was poorly correlated with personal measurements for this pollutant. NO_2 is formed in part by atmospheric transformation, whereas NO is a primary emission so the surfaces for NO had a stronger source signal (in this case traffic) and the NO_2 surfaces were more diffuse. Because the traffic relationship for NO_2 is relatively weak compared to NO, the NO_2 signal from traffic is likely hidden by the effects of indoor sources and lower spatial variability.

Ambient monitoring based estimates are appropriate (for highly time-varying pollutants: NO, fine particles) when only temporal variability in exposure is important, but these estimates reflect less spatial contrasts even when there is a relatively dense monitoring network, as in this study region. In **Chapter 3**, individual-level determinants of exposure (i.e. gas stove, air conditioning, cooking) were included with outdoor estimates (using land-use regression and ambient methods) in regression models to predict personal exposures. An important result is that the magnitude of the effect of outdoor model estimates (using land-use regression and ambient) on personal measurements was relatively robust to the inclusion of other individual determinants of exposure. For example, for NO, an interquartile change in the outdoor land use regression estimate predicted a 63% change in personal measurements in the unadjusted model (model for land use regression including home and work locations) and a 52% change after adjusting for other individual determinants (for NO: gas stove, time outdoors). Also for NO, the ambient outdoor estimate (using inverse distance weighting) predicted a 21% change in personal NO, unadjusted, and a 19% change after adjustment. For NO_2, outdoor land use regression estimates predicted an 11% change in personal NO_2, unadjusted and 12% after adjustment. For $PM_{2.5}$, ambient fixed-site estimates (using inverse distance weighting) predicted a 22% change, unadjusted, and a 20% change after adjustment. The exception was personal absorbance samples (26% unadjusted) which seemed to be more strongly affected by outdoor modeled $PM_{2.5}$ after adjusting for wood smoke (65%, adjusted). This is reassuring for studies where no individual factors (i.e. home characteristics) are available and exposures are based only on ambient outdoor estimates.

Impacts of Mobility and other individual factors

Home was the dominant location (mean= 68%, SD=13% of total time) for study subjects based on time-activity results. This supports the use of home-based proxies for exposure assessment (especially where no other location information is available). These results are similar to other studies using random samples from the population (e.g. NHAPS, CHAPS) (10). This thesis (**Chapter 2**) also demonstrated that including mobility (using work location) improved exposure models when compared to personal samples (NO: Pearson's r=0.49 home only, r=0.54 home and work). Unfortunately, due to limitations of the GPS equipment, the impact of including exact mobility (i.e. transit and locations other than home or work) based on GPS route data could not be fully assessed. When examining only a subset of people who spent most (>65%) of their time at home, correlations between land use regression estimates and personal measurements were higher for all pollutants compared with results for all women in the study. For $PM_{2.5}$, the land-use regression model was non-significant in correlations with personal measurements using all samples (r=0.07), whereas there was a modest correlation when limiting to less mobile subjects (r=0.30). These results indicate that exposure models based on home location only are more accurate when subjects spend more time at home. Additionally, including a secondary location where people spent a majority of their time (work or school) also improved exposure models.

Further results from the simulation described in **Appendix C** suggest that time in transit is unlikely to have a large impact on exposure for our study population. Similar results were found in a population-based simulation study modeling changes in exposure due to different commuting patterns conducted by other BAQS researchers (11). Future exposure models should consider using time-weighted secondary locations (i.e. work or school) rather than only home-based exposures.

In **Chapter 3**, regression models found that presence of a gas stove at home was the strongest predictor of personal measurements for all pollutants. This is consistent with other studies showing that gas stoves have a significant impact on personal exposure measurements (12). Cooking, ventilation or room volume determinants were also significant in models for personal absorbance and/or $PM_{2.5}$. Outdoor exposure estimates, using land-use regression and/or ambient measurements, that were significant in analyses from Chapter 2 remained significant in personal measurements even after adjusting for individual factors. These findings improve our understanding of sources of exposure to air pollutants among pregnant women and support the use of outdoor-based (especially at home) estimates as proxies for exposure.

Activity patterns of pregnant women

Numerous studies suggest that *in utero* exposures, including exposure to air pollution, can have a significant impact on future health (13). Although location and time-activity data has been used to model exposure to specific contaminants in epidemiological studies, little information is available about time-activity patterns of pregnant women. In **Chapter 4**, increasing weeks of pregnancy was a significant predictor for increased time spent at home. Specifically, there was a 1 hour per day increase in time spent at home for each trimester of pregnancy, after adjusting for income, work status and other children in the family. No other measured activities (time outdoors, time in transit modalities or time in other indoor locations) were related to weeks of pregnancy. As pregnant women tend to spend more time at home during the latter stages of pregnancy, future exposure and epidemiological research should consider the potential increase in home-based exposures (i.e. indoor air pollution or chemicals in the home) late in pregnancy, and increased confidence in exposure proxies based on home locations or characteristics during the same period. When considering exposures during different periods of pregnancy, home-based estimates may be more accurate for the later months of pregnancy (i.e. less error).

Recommendations for future work

More "measured-to-modeled" evaluation studies are needed to confirm the findings in this thesis. Specifically, the ability of land-use regression to predict personal exposure can be better judged when there are additional evaluation studies in other locations and among other populations.

While this thesis compared personal samples to modeled exposures, measurements were relatively short-term. Future evaluation studies would benefit from increased number of repeated samples per person (and/or longer duration of sampling) to better assess the applicability of land-use regression to chronic exposure studies. This study was limited in characterizing the ability of the land-use regression to capture spatial variability *alone* because time factors needed to be included in the land-use regression models to account for differences in sampling times. A possible, although logistically difficult, solution for this would be to collect all personal samples during exactly the same time period(s).

The women who participated in the sampling study were self-selected and not a random population sample. While this is unlikely to bias estimated exposures to outdoor air pollution, it may have affected the individual determinants or activity factors. Specifically for the activity pattern results, a randomly sampled study would better characterize the activities of pregnant women as similar or different to the general population.

Conclusions and Significance

In this thesis, air pollution models used for population-level exposure assessment were moderately predictive of empirical personal measurements. Personal measurements of NO showed consistent associations with both land-use regression (high spatial variability) and ambient monitoring-based (high temporal variability) models. Personal absorbance and fine particulate ($PM_{2.5}$) measurements were only predicted by ambient monitor-based $PM_{2.5}$ estimates whereas personal NO_2 was marginally associated with annual average land-use regression model estimates only. However, relationships between ambient modeled exposures and personal samples were not strongly affected by adjustment for indoor sources and individual factors, despite these factors being associated with measured exposure. Home gas stove, cooking, air conditioning and wood smoke were also significant in predicting personal exposures. Mobility effects (assessed by time spent at work/school) were important in improving exposure models. Lastly, time spent at home among pregnant women increased over the course of pregnancy.

Overall, the results from this thesis (a) support the use of current methods for assessing exposure to air pollution and (b) indicate areas of improvement for population-level air pollution exposure modeling in general and specifically for exposures of pregnant women.

(a) Support for current methods of air pollution exposure assessment

These results support the use of current methods for air pollution exposure assessment in the following ways. Firstly, in this study, estimates of exposure at the home address based on traffic-based land use regression models or ambient pollution measurements, were found to contribute to differences in personal exposure between individuals even in a relatively low pollution city such as Vancouver. For example, an interquartile range difference in land use regression model estimates of exposure at home, was associated with a 62% change in measured personal NO and a 7% change in NO_2 exposures. Similarly an interquartile range increase in ambient monitor-based estimates of exposure at the home address was associated with a 41% change in personal NO, a 14% change in Absorbance and a 12% change in $PM_{2.5}$.

Secondly, these results were relatively robust to adjustment for individual activities and indoor sources which increases our confidence in the use of modeled home outdoor concentrations alone to detect differences in personal exposure to air pollutants in epidemiological studies.

Thirdly, this thesis demonstrated, as expected, that the influence of outdoor pollution using monitor-based models on personal exposures was driven by temporal fluctuations in outdoor pollution. These results support using exposure models with high temporal variability specifically for acute exposure studies where time-varying aspects of exposure are of interest and for pollutants (e.g. $PM_{2.5}$) that have low spatial but high temporal variability.

Fourthly, results were most consistent across methods (land-use regression and ambient models) for NO, a primary and highly spatially variable pollutant. This suggests that this pollutant is an effective marker of personal exposure to traffic-based pollution. The high spatial and temporal variability of NO, specifically, may make this a useful pollutant for epidemiological studies for acute or intermediate length exposures. This thesis also presented results showing that only the *annual* land-use regression model for NO_2 was associated with personal exposures. This suggests that individual variability in personal NO_2 exposure from outdoor pollution is due to spatial differences between individuals rather than differences in time. An implication of this result is that NO_2 might be an effective marker for epidemiological studies of chronic exposures to traffic-related pollutants.

(b) Improvements to existing modeling methods

This thesis work has implications for improving exposure models used to predict individual air pollution exposure. Some implications relate to general exposure assessment (moving from exposure measures to models) and others are specific to pregnant women.

Including time trends in land-use regression models

By design, land-use regression models address spatial variability more so that estimates based upon ambient monitoring networks. The results from this thesis indicated that combining a land-use regression estimate with a monthly trend increased the ability of the model to detect differences in personal exposures. This supports the use of temporal adjustment trends for land-use regression models, specifically when the exposure periods of interest are shorter in duration. In this case, a monthly trend was sufficient to detect these differences. However, results showing that ambient models using the exact 48-hour time period of exposure were most highly correlated with personal exposures (of the same duration) suggest that more precise time trends (e.g. daily or diurnal) might be informative for a land-use regression model. Specifically, this could be useful for examining shorter term exposure windows. For example, during pregnancy, major changes in fetal development take place over a relatively short duration and increased precision in exposure assessment for these time-windows could allow for better detection of adverse health impacts. Or, for considering population exposures during transit time or occupational exposures for those spending most of their time on roads (e.g. bus drivers, taxi drivers), a rush-hour land-use regression could be developed and might be informative. A diurnal (night/day) trend could also be developed that would adjust a land-use regression surface depending on the length of the day at different times of year.

Another way to include a high variability both spatially and temporally would be to combine both land-use regression and ambient monitoring exposure metrics in the same health effects model. In this thesis, these two metrics were only marginally correlated and were combined in the same model for predicting personal exposures. This approach may not be appropriate depending on the data but should be considered for future studies.

Including secondary locations (e.g. work or school) in exposure modeling

Exposure assessment based on home location only would be improved by including secondary (work or school) locations where people spend time. In this thesis, limiting to the least mobile subjects showed highest correlations overall between home only models and measures indicating that the home-only models perform best for subjects with low mobility. Models accounting for mobility using a secondary location (work or school) improved associations between models and measures (land-use regression) when using the entire population. These result imply that (1) home only models work best for the least mobile populations (e.g. seniors) and (2) that including a simple level of mobility (secondary location) improves exposure assessment for working populations.

Including individual activities and indoor sources

This thesis demonstrated that individual activities and sources (e.g. gas stove) were important in predicting personal exposures. Including these factors would likely improve exposure assessments, but these data are rarely available at the population level. The use of property assessment or taxation records could be a possible source for individual-level determinants (e.g. gas stove) that could be used in population exposure models. Specifically for the pregnant women in this study, home gas stove presence was an important predictor of personal exposures to all pollutants and increased home volume or ventilation is likely to reduce exposures in the home. The distribution of individual factors (e.g. gas stoves) in a study population should be considered when developing exposure models as potential sources of error or bias. However, this thesis did not show a significant impact of indoor sources or individual activities on attenuating the effects of outdoor air pollution on personal exposures.

Implications for exposure assessment during pregnancy

This thesis demonstrated an increase in time spent at home during the latter periods of pregnancy. When assessing exposures for future studies of pregnant women, this increase in time spent at home has implications. For example, exposures to home-based contaminants (e.g. environmental tobacco smoke at home) may increase during later stages of pregnancy. On the other hand, this increase in time spent at home could lead to lower error in using home-based exposure models to predict exposures during the last months of pregnancy because of this decreased mobility. The key conclusions and recommendations from this thesis are summarized in Table 5.1.

Traffic-based and ambient outdoor pollution exposures contributed differences in personal exposure between individuals even in a relatively low pollution city like Vancouver. This increases our confidence in results from epidemiological studies in this city that observe associations between adverse birth outcomes and modeled exposures of pregnant women. Improving air pollution exposure assessment will also increase our ability to quantify the impacts of air pollution on human health, not only for pregnant women, but for everybody. Hopefully, this will further support efforts to reduce population exposure to air pollution and reduce impacts on our health.

Figures and Tables

Table 5.1 Key conclusions and recommendations from this thesis

Support for current modeling methods:	
1	Differences in outdoor pollution were detected in personal measurements using both modeling methods: land-use regression and ambient monitor-based models
2	These differences were relatively robust to individual factors
3	Ambient monitor-based models perform well for predicting differences in time for personal measurements
Recommendations and considerations for future exposure assessment models:	
1	Include secondary locations (work or school) to account for mobility and/or use home-based models for subjects with low mobility
2	Consider further applications of time-trends in land-use regression
3	Focus on NO for epidemiological studies where both a high degree of spatial and temporal variability in exposure is important. Some confidence in NO_2 for chronic exposures.
4	Limited need to include individual determinants in population models
5	Increase confidence in home-based exposure models during late pregnancy because of decreased mobility
6	Increase awareness of home-based exposures (that may have adverse health impacts) for pregnant women during late pregnancy

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Appendix A Detailed Methods, Sampling and Exposure modeling

This thesis involved two types of air pollution data: personal measurements and ambient modeled pollution data. The personal measurements were obtained through a year-long personal monitoring study called the Pregnancy Health and AIR Pollution (PHAIR) Study. The PHAIR study also collected information on activity patterns, home and work building characteristics and demographics for the study group. The ambient air pollution data used in this study was obtained from two sources: a previously developed land-use regression model (1) and daily pollutant measurements taken at air quality monitoring stations located in the Greater Vancouver Regional District.

A.1 PHAIR Sampling Study and Data Collection

The PHAIR study involved 62 pregnant women (non-smokers living with non-smokers and healthy pregnancies) recruited through yoga/pilates classes, prenatal classes, posters (community centres, health testing labs, drugstores), midwifery clinics and health practitioners. Participants were limited to those living in the Greater Vancouver Regional District. Since the land-use regression model reflects variability in traffic-based pollution, attempts were made to recruit participants whose residential addresses captured the variability in the model. We attempted to ensure that the participants who were included in the study had home addresses which covered both the high and low exposure categories as predicted by the model. High exposure areas were identified by participants' addresses >= 90^{th} percentile of the estimated exposures from the land-use regression model (NO_x) and low exposure areas were identified as those <= 25^{th} percentile of the exposure model data. Subjects were retained in the study even if they moved between sampling sessions as long as they remained within the study area. The research protocol (including questionnaires, time-activity log and consent forms) was approved by the UBC Behavioral Ethics Review Board (Approval # B05-0441).

The women wore personal air monitoring equipment and carry a GPS-enabled datalogger[1] on two or three 48 hour occasions spaced 3 months apart, ideally during the 1st, 2nd and 3rd trimesters. Due to the difficulty of recruiting women in their first trimester, most participants were in their second trimester participants and were asked to complete two measurements (2nd and 3rd trimester). On the first sampling session, we obtained a signed consent and spent about ½-1 hour completing questionnaires, answering questions and explaining the equipment. Sampling was scheduled so that daytime sampling was on weekdays only; i.e. during a 48-hour period between Sunday evening and Friday evening. Data collected on the first sampling session *only* included:

1. Self-administered "Participant Questionnaire"
2. Technician administered "Dwelling Information Questionnaire"

At subsequent sampling sessions, participants were asked to confirm that their home or work location had not changed. If there were changes in the home or work location (other than change in employment status, i.e. Working part-time or not at all), then the dwelling information questionnaire was re-administered at the later session. Data collected on **all sampling sessions** is listed in Table A.1.

Table A.1 Summary of data collected in each sampling session (PHAIR Study)

Sample Collection	Measurement	Sample Analysis or Extraction Method
Ogawa passive diffusion sampler	NO, NO_2, NO_X	Ion chromatography
Teflon 37mm filter loaded into PEM; connected to Leland Legacy Pump at 5 L/min	Fine particulate ($PM_{2.2}$)	Gravimetric analysis
	Absorbance (filter blackness)	Reflectance
	Levoglucosan	
Delorme BlueLogger GPS	Individual Mobility data	GIS analysis (ArcGIS)
Time-activity log (self-administered)	Activity data	n/a

[1] GPS dataloggers are passive receivers of satellite signal data (similar to a tv receiver) and there is no known risk to pregnant women from this device or any of the air monitoring equipment.

A.1.1 Questionnaires and Time-activity Data

Copies of the questionnaires and the time-activity log are attached in Appendix B. The self-administered "Participant Questionnaire" data was used to characterize the study population. Questions related to: age, due date, ethnicity, parity, income, education level, industry type (of employer), job type and status (full-time, part-time, not working). The "Dwelling information questionnaire" was administered by the technician and collected detailed information about participants' home building (age, type, ventilation, size, windows, carpets, heating, gas stove, attached garage, fireplaces, floor), primary and secondary family motor vehicle (type, year, model), and work building (age, type, ventilation, size, windows, proximity to traffic, heating, office floor, underground garage, particle sources at work). If participants reported that they worked in more than one location, they were asked to complete the Dwelling information questionnaire (work information) for their primary work location or the location where they worked during sampling.

The women completed a time-activity log during each 48-hour sampling period. The technician explained how to complete the time-activity log and provided written instructions. For every ½ hour period during sampling, participants indicated their:

- current location (indoor at home, work, other or outdoor)
- transit activity (time of transit and method: car, bus and bus type (diesel, electric or skytrain), walk, other); if "other" was indicated, participants always noted bicycling in the notes column so that field was coded later as "bike".
- whether they are currently nearby to cooking, smoking
- whether they are wearing the sampler
- whether the windows are open near them
- current level of activity (high, medium, low); low is "at rest" (sleeping/rest); high is the highest level of physical activity they do

A sample of a line from a completed activity log is shown in Figure A.1. Omitted from the drawing is a "notes" column where participants could indicate any specific information about their activities during that half-hour segment. Since events can be less than ½ hour, participants were told to indicate in the minutes space the time associated with the transit event. If more than one activity (i.e. Figure A.2: Bus and Walk) was specified during a half-hour, then both activities were assumed to take 15 minutes each.

Figure A.1 Sample Activity Log; 30 minute segment

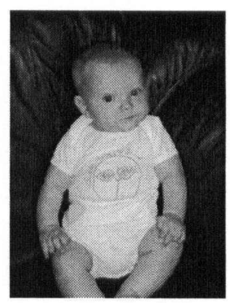
Time	Indoors			Outdoors		Transit						Activity Level	Cooking		Tobacco Smoke		Windows Open		Wearing Sampler	
	Home	*Work*	*Other*	*Near Home*	*Away*	*Car*	*Bus*	*Bus Type**	*Walk*	*Other*	*mins*	*Lo Mid Hi*	*Y*	*N*	*Y*	*N*	*Y*	*N*	*Y*	*N*
8-8:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y	N	Y	N	Y	N	Y	N

Figure A.2 Sample Activity Log with 2 Activities specified in 30 minute segment

Time	Indoors			Outdoors		Transit						Activity Level	Cooking		Tobacco Smoke		Windows Open		Wearing Sampler	
	Home	*Work*	*Other*	*Near Home*	*Away*	*Car*	*Bus*	*Bus Type**	*Walk*	*Other*	*mins*	*Lo Mid Hi*	*Y*	*N*	*Y*	*N*	*Y*	*N*	*Y*	*N*
8:30-9 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other	15	Lo Mid Hi	Y	N	Y	N	Y	N	Y	N

For each activity log, the total minutes that each activity occurred was calculated. Each event was divided by the total minutes in the activity log to determine the percentage of the sampling time that each activity represented. We attempted to ensure that all sampling sessions were as close as possible to 48 hours (2880 minutes). All activity percentages were multiplied by 24-hours and results shown in hours/day.

Figure A.3 Baby and thank-you gift



A post-birth follow-up questionnaire was either mailed or completed in person following the birth. At this time, participants received a small thank-you gift (baby clothing) which is shown at right.

A.1.2 Personal Monitoring

The personal air monitoring equipment and GPS-datalogger (Figures A-3 to A-6) was contained in a small backpack or shoulder bag. Participants were offered a choice of several different styles of bags (either a backpack, purse or single-shoulder pack). Subjects were encouraged to wear the sampler while moving about, but were allowed to place the equipment on a table or chair near their current work/home area. At night, the women were allowed to place the sampler outside the bedroom if the noise was disturbing to them. All participants were reminded that they could put the sampler down as needed but to always place it on a chair or table *not* on the floor.

Figure A.4 Sampling Equipment and Bag

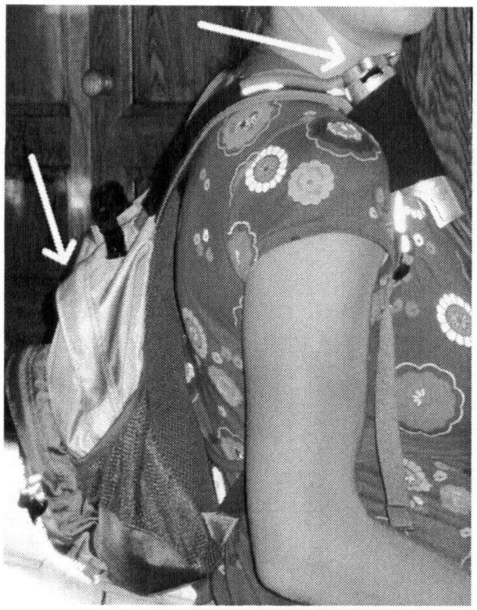


Figure A.5 GPS Datalogger case, Ogawa sampler and PEM $PM_{2.5}$ sampler head

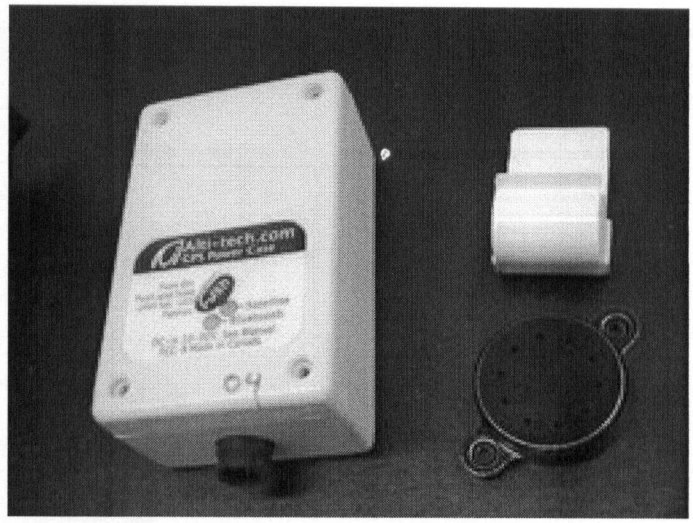


Figure A.6 SKC Leland legacy air sampling pump and noise-reducing case

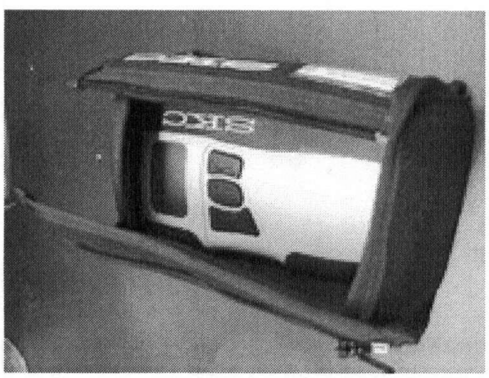


Figure A.7 GPS datalogger inside battery case

Sampling equipment (pumps) were enclosed in a noise-reducing case. The Ogawa sampler was mounted in a small clip and attached to the shoulder strap of the backpack or bag. The air sampling methods used in this study are commonly used in occupational or environmental hygiene and were selected based on:

- availability of equipment at the School of Occupational and Environmental Hygiene at UBC,
- lowest possible noise and vibration during sampling,
- a 48-hour sampling duration.

A.1.2.1 Particulate Matter Samples

Personal Particulate Matter (PM) samples were measured with a Personal Environment Monitor (PEM, MSP Corp) that was developed by Marple and colleagues (2). The PEM $PM_{2.5}$ sampler was loaded with a pre-weighed 37-mm 2um-pore size Teflon filter connected to a battery powered sampling pump (SKC Leland Legacy) set to a flow rate of 5 L/min. Pumps were enclosed in a protective nylon case to minimize noise. Because the lab already had five Leland Legacy pumps and because of its >50 hour continuous run-time (long battery life), we decided to use this pump rather than purchase new pumps. However, the Leland Legacy minimum flow rate is 5 L/min. The PEM $PM_{2.5}$ sampler is designed to be run at a flow rate of 4 L/min in order to obtain a 2.5 □m cutpoint. By running the SKC pump at 5 L/min, the measured particulate sample had a 2.2 um cutpoint rather than a 2.5 □m cutpoint. The calculation of the PM cutpoint for a 5 L/min flow rate is shown in Appendix D. It was acceptable in this study to measure $PM_{2.2}$ rather than the more standard $PM_{2.5}$ for the following reasons:

1. Key project goal was to compare personal measurements to modelled estimates for Absorbance and NO/NO_2 ***not* $\mathbf{PM_{2.5}}$)**
2. Absorbance is dominated by very fine particulate. Measures of filter absorbance of co-located PM10 and PM2.5 filters are be highly correlated ($R^2=0.99$) (3). Hence, a small change in PM cutpoint will not alter measured absorbance values.

Each PEM assembly was tested for leaks prior to sampling. The flow rate of each sampling setup (PEM and sampling pump) was verified prior to sampling using a Dry-Cal. The flow rate was adjusted using the Leland Legacy calibration flow adjustment settings to achieve a 5.0 L/min (+/- 0.01) flow. At the end of the sampling session, the flow calibration was verified using a Dry-Cal. The final flow rate was noted, as was the total time (minutes) recorded by the pump. The total time in minutes recorded by the pump was the time that the pump was operating (drawing air) during the sampling session. To calculate the volume of air drawn by the pump we averaged the initial and final flow rates and used the following calculation. $Vol = ((f_{initial} + f_{final})/2\ ) * t$

Variable	Description	Source
t	Total time pump operated (min)	From Leland pump memory
$f_{initial}$	Initial flow rate (L/min)	Assumed to be 5.0 L/min
f_{final}	Final flow rate (L/min)	From post-sampling calibration with Dry-Cal
Vol	Volume of air (L)	Calculated

Table A.2 Variables used to calculate air concentrations

The PM samples were collected on 37mm filters that were analyzed by standard gravimetric methods. Each filter was weighed 3 times pre and post sampling. The difference between the average of the pre and post sample weights was the mass of the particulate on the filter. Laboratory quality control filters were weighed during each weighing session and every 10th filter was treated as a field blank. Eight filters were designated as laboratory blanks. PM masses (□g) were converted to concentrations □g/m3) by dividing the PM mass by the volume of air sampled by the pump.

We calculated the limit of detection (LOD) as three times the standard deviation of the laboratory blanks or 12 μg (PM Mass) or approx 1 μg/m^3. We did not do replicated sampling for PM but other studies using similar methods reported a coefficient of variation (CV) of 8.4 % (4).

A.1.2.2 Black Smoke

After weighing, the blackness of each filter was measured. The "blackness", often referred to as Black Smoke (BS), is an indicator of the elemental carbon content (a major component of diesel soot) of the particles on the filter (5,6). The blackness was measured using a Smoke Stain Reflectometer (Diffusion Systems Inc.) to measure the reflectance of the filters according to a standard method (SOP ULTRA/KTL-L-1.0 1998). Each filter was measured in five locations and averaged to give R, the intensity of reflected light from the exposed filter. Five control filters are measured and averaged to give R_0, the intensity of reflected light from the control filters. The absorbance, a, is calculated by the formula: $a = (A/2V)\ln(R/R_0)$; where A is the area of the filter (m^2) and V is the volume of air sampled (m^3). The final absorbance measurement is unit-less and is reported in exponential form (10^{-5} m^{-1}). Previous sampling demonstrated a high correlation between co-located elemental carbon measurements and filter absorbance measurements in the Greater Vancouver area (7). Field and laboratory blanks were also measured for absorbance. The limit of detection of absorbance was calculated as 0.1 10^{-5} m^{-1} based on 3 times the standard deviation of the blanks. The CV of the method from previous studies has been reported as 6%.

A.1.2.3 Levoglucosan: Wood Smoke tracer

As a final step, the filters were analyzed for levoglucosan (1,6-anhydro-β-D-glucopyranose) using methods described by Simpson et al (8). Levoglucosan is emitted from combustion of biomass and is commonly used as a tracer for wood smoke (9). Levoglucosan measurements, were offered as potential effect modifiers in deterministic models of personal (PM and 'soot') measurements with the intent that high levoglucosan measurements would indicate samples influenced by wood smoke.

A.1.2.4 $NO_X/NO_2/NO$

NO, NO_2 and NO_x was measured using small passive samplers (about 5cm diameter, 16 g) (Ogawa USA Inc.) clipped to the shoulder strap of the sampling bag. These samplers are barrel-shaped and contain two filters; one captures NO_2 and the other, NO_x. Filters were pre-loaded into the samplers and then stored in air-tight plastic containers in the fridge until sampling. After sampling, filters were extracted in de-ionized water and nitrite concentration was determined by ion chromatography. At least 3 field blanks were analyzed in each analysis run and 10% of samples were run in duplicate for detection limit and error calculations. Ogawa samplers were used in Vancouver, BC to provide the initial ambient monitoring data for the development of the BAQS land-use air pollution regression model (1,7).

About 10 % of the samples were treated as field blanks and 5% as analytic (lab) blanks. A limit of detection was calculated based on the mean of the lab blanks + 3*SD of the blanks. No field correction was applied. Due to the fact that field blanks were included sporadically, it was impossible to correct for field contamination on the sampling day. As such, field error was likely to be random and should not affect comparisons to modeled estimates. The final NO and NO_2 concentrations are reported in ppb and the limit of detection was 0.45□g NO and 0.20□g NO_2 mass. Co-located sampling (3 pairs of 2 samples) gave a CV of 5% for the method.

A.1.2.5 Mobility Data – GPS Datalogger

The GPS dataloggers (BlueLogger, DeLorme Inc.) recorded latitude, longitude, time, speed every 5 seconds while a GPS signal was detected. We replaced the built-in battery from the datalogger with a battery pack (Alti-tech Inc.) to extend the continuous run-time to at least 48 hours. Prior to each sampling session, we confirmed that a GPS signal had been acquired near the location of the start of the session. The logger was left in the bag with the sampling equipment and turned off at the end of sampling. We placed the GPS unit in the bag in an orientation that was supposed to maximize the datalogger's internal antenna but subjects were *not* instructed to watch the GPS logger in any way or to check if a signal was being obtained. The GPS data was downloaded at the end of each sampling session. All GPS Route data was assessed for completeness prior to analysis. GPS routes with less than 30 hours, any gap greater than 4 hours and greater than 2 km or other time gaps which could not be explained by the activity log were excluded from analysis. The GPS loggers' should be accurate within about 10 m with a full signal (3+ satellites) and clear sky-view. In this study, we obtained a precision of +/- 30 m on average when the signal was established.

All GPS Route data was be assessed for completeness prior to analysis. GPS routes with less than 30 hours, any gap greater than 4 hours and greater than 2 km or other time gaps which could not be explained by the activity log were excluded from analysis.

A.2 Ambient Air Pollution Exposure Estimates

For the BAQS cohort study, air pollution exposure was estimated using two methods: (1) Land-Use Regression Models and (2) Ambient Monitoring Station Data Interpolation Models. For the Ambient Monitoring Interpolation Models, there were two types of approaches used: Nearest Monitor and Inverse Distance Weighting.

Where possible, methods used to assign exposure for these models were replicas of those used for the population-based cohort study (BAQS). However, since more detailed personal information was available for the women in the PHAIR study, it was possible to compare the effect more individual-level exposure assessment on the exposure estimates. A cohort-equivalent exposure assessment method was employed for both land-use regression and ambient monitoring approaches. In both cases, more refined exposure assessment was also employed and compared to the cohort-level approach. While the main focus of this work was not the comparisons between exposure assessment methods, it was important to understand if any lack of association between the personal measurements and modeled estimates was due to the models themselves or the exposure assessment methods used. The following table lists the methods which are explained in more detail in the following sections.

Table A.3 Exposure Assessment Methods in PHAIR study

Ambient Air Pollution Model	Cohort-comparison Exposure Assessment Method	Individual-level Exposure Assessment Method
1. Land Use Regression Model	Postal code Geocoding	Home Address Geocoding
2. Ambient Monitoring Station Data Interpolation Models a. Inverse Distance Weight b. Nearest Monitor	Monthly: 30 day average centered on sampling session (14 days before-after)	Time-specific: Average of the model during 48-hour sampling period

A.2.1 Land-Use Regression Model Exposure Estimates

A.2.1.1 Land-Use Regression Models

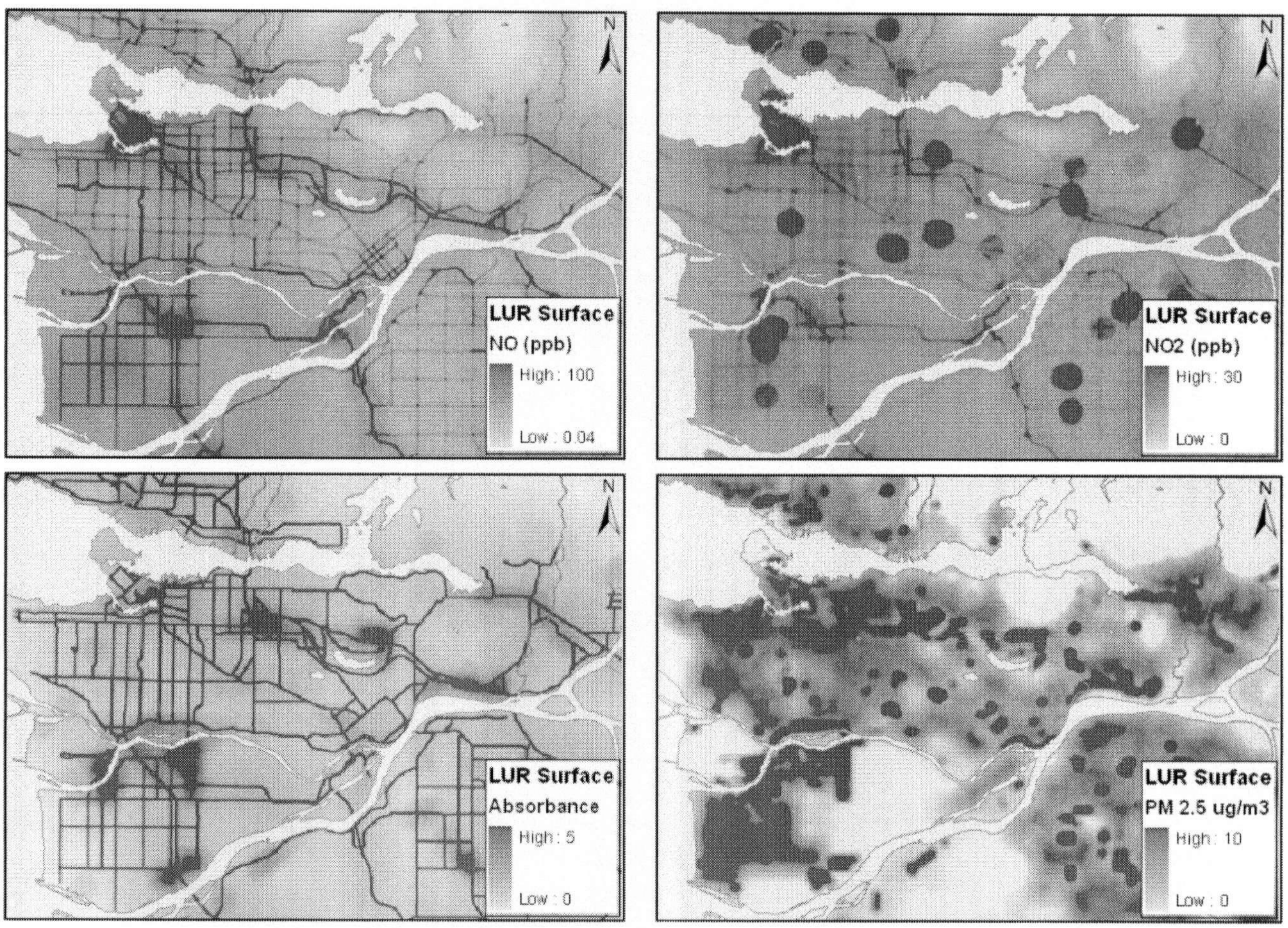
The land-use regression surfaces used in this project were raster (continuous) surfaces with a resolution of 10x10 m cell size and covered the whole of the Greater Vancouver Regional District. The LUR surfaces were generated by Sarah Henderson and Dr. Michael Brauer (1,10); a brief description of the approach will be provided here.

A sampling campaign in 2003 (112 samplers for NO, NO_2; 25 samplers for Absorbance and PM) provided the measurement data that was used to develop the model. Sampling sites were selected using mathematical algorithms to cover the variability in concentrations and other variables of interest (e.g. population). Sampling times were selected during weeks in the spring and fall that were within 15% of the annual average mean. Geographic predictors (n=98) were generated for the study area based on the geographic characteristics at the study sites. Variables represented the following (e.g.): road lengths, road density, land use category, population, elevation, and traffic density. Afterwards, a regression approach was used to identify geographic variables that were predictors of the measured results. A final set of predictors was identified using a step-wise regression; model R-squares ranged from 0.49-0.63. The coefficients and intercepts were summed with the predictor surfaces in ArcView (ESRI v 3.0) to generate the final land-use regression surfaces. For the purposes of this analysis, only the surfaces based on road length (rather than road density) were used. The final surfaces were smoothed using ArcGIS Spatial Analyst (ESRI v.9.0 2004).

"Neighbourhood, Focal Statistics" tool and a resolution of 7 cells squared. This effectively smoothed out any abrupt transitions in the surface.

Each surface contains the annual average pollutant concentration in the area; one surface per pollutant (see Figure A.4). Because the surfaces represent annual pollution, a seasonal trend was applied for shorter-term exposure periods. Using ambient monitoring data from 1998-2004 (11), a seasonal trend was generated. The seasonal trend has monthly and yearly coefficients that could be applied to the land-use regression estimates. Land-use regression estimates which have been adjusted by these trends are referred to as "seasonally-adjusted" in the analysis.

Figure A.8 Vancouver Land Use Regression Surfaces (shown for PHAIR Study Area)

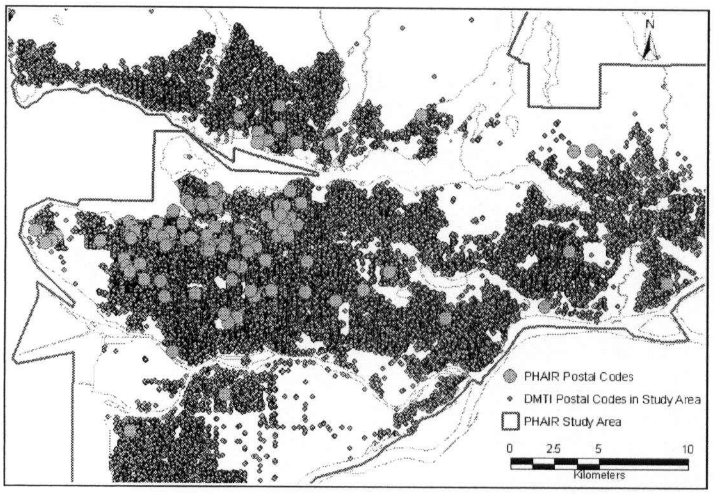


A.2.1.2 LUR Estimates: Exposure Assessment at Home & Work Location

Land-use regression estimates were assigned to participants home and work locations based on (1) their postal codes and (2) their geo-coded addresses. Home and work postal codes and addresses were obtained from the participants' responses on the Dwelling Information Questionnaire. Using the postal code method is comparable to the cohort study since address-level information is not available in the population study. In urban areas, postal codes can represent an area as small as an apartment building or a block face.

All postal code locations (centroids) in Canada were obtained from the CanMap Multiple Enhanced Postal Code (DMTI Spatial Inc.) obtained from the UBC Geography Data Library. A subset of the DMTI Postal code layer was created that included only the work and home postal codes for the PHAIR study participants. Land use regression values were obtained at each of these **postal codes** using ArcGIS tool "Extract Values to Points" which extracts raster (LUR surface) values at the postal code point locations[2].

Figure A.9 All DMTI Postal Codes and PHAIR Study Postal Codes

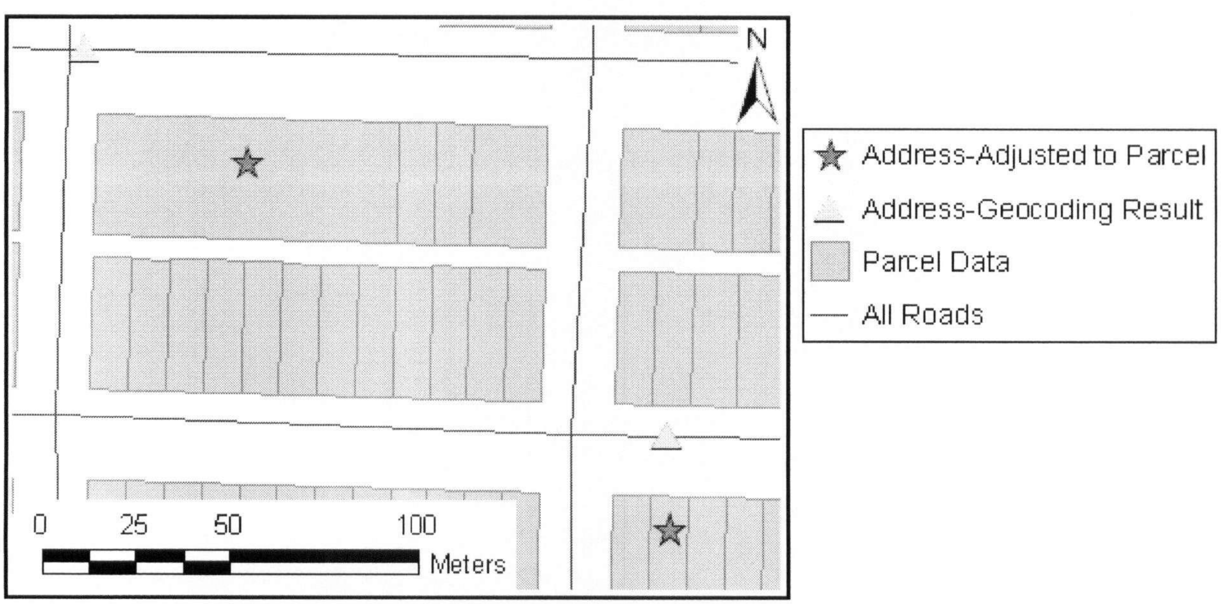


The PHAIR study home and work **addresses** were geocoded in ArcGIS using the CanMap Streetfiles, 2001 (DMTI Spatial Inc.) road network and address locator. The automated process was successful for about 40% of the addresses; the rest had to be manually located or adjusted. In some cases, the subjects' addresses were on roads that were not included in the DMTI road network (new subdivisions). These locations entered into Google Earth to obtain a

[2] I also evaluated the use of a 50 m. buffer around every point and averaged the LUR values in that 50 m buffer. However, the smoothing steps taken on the whole surface effectively negated the need to buffer around the locations by removing any abrupt transitions in the surface. Comparisons between using 50 m buffers and the values extracted exactly at the point locations from the smoothed surface yielded Pearson R of 0.9995 so the buffering was dropped in favour of using the smoothed surfaces.

lat-long and then manually added at the appropriate location in ArcGIS. When geocoding addresses, ArcGIS uses road network segments to locate addresses and positions the points directly on the road segment. The triangles shown in Figure A.6 are geocoded points from ArcGIS address geocoding. The road network contains the left and right-most addresses for every road segment. The geocoding process calculates the percentage that the requested address is offset from the left or right end, and places the address there. Because the land-use regression surface values are linked to road locations, using the geocoded locations directly on top of the road would over-estimate exposure. Additionally, for large building footprints, the geocoding may mis-locate addresses by as much as 100 meters. The parcel data was obtained for the study area and contained lot boundaries and addresses. All home and work addresses points were verified manually and adjusted to the center of the street-facing portion of the land-use parcel for each address. The land-use parcel data was obtained from Eleanor Setton at University of Victoria (12). This dataset combined land-use attribute data from BC Property Assessment with parcel data obtained from each municipality/jurisdiction (2004-2005). In some work locations or apartment buildings, land-use parcel data did not exist for the exact address. In these cases, the address was shifted off of the street segment to a location nearest to the lot with the closest address on the same side of the street. Often these were cases where a large lot parcel was indicated which likely contained the specified address even though it was not explicitly specified in the dataset.

Figure A.10 Geocoded Address and Adjustment with Parcel Data



As for the postal codes, land-use regression model estimates for NO, NO_2, NO_X, PM2.5 and Absorbance at the address (adjusted using parcel data) points were extracted using the ArcGIS tool "Extract Values to Points". All values (except Absorbance) were then seasonally adjusted using the monthly and yearly trend parameters for each pollutant according to the month and year of the sampling session. In cases where participants did not work, no work postal code or work address estimate was included.

A.2.1.3 Incorporating Mobility in LUR Estimates: Combining Home & Work Estimates

The estimates at home and work locations were weighted by the percentage of time spent at home and work from the participants' time-activity log. This approach assumed participants' spent 100% of their time at either home or work. For example in the table below, an individual's land-use regression "Combined home+work" exposure estimate would be calculated as follows:

1. **Calculate Home and Work Fraction using %time at home and work from time-activity log.**
   a. **Home Fraction** = $T_{home}/T_{home+work}$
   b. Work Fraction = $T_{work}/T_{home+work}$
2. Calculate Combined LUR Estimate (note: "Poll" refers to pollutant. This process is repeated for each pollutant).
   a. $\mathbf{Poll_{home+work}} = (Poll_{home} \times Fr_{home}) + (Poll_{work} \times Fr_{work})$

<u>Example Calculation:</u>

Step1:

%Time Home	%Time Work	Total Time Home + Work	Home Fraction	Work Fraction
T_{home}	T_{work}	$T_{home+work}$	Fr_{home}	Fr_{work}
72%	19%	91%	79%	21%

Step 2:

LUR Home	LUR Work	Time-weighted Home LUR	Time-weighted Work LUR	Combined Home+Work Estimate
$Poll_{home}$	$Poll_{work}$	$Poll\_tw_{home}$	$Poll\_tw_{work}$	$Poll_{home+work}$
15.2	25.2	0.79x15.2=12.02	0.21x25.2=5.25	17.29

A.2.1.4 Incorporating Mobility in LUR Estimates: GPS "Exact" Route Estimates

The GPS route data from the study participants' was processed in SAS and incomplete routes were excluded from analysis.

The GPS dataloggers did not perform as expected; in many cases, either no data was recorded, or there were large spatial or temporal gaps in the route data. As a first pass, routes were excluded because they were missing more than 16 hours from either the start or end of the sampling session. For each point remaining, the distance to the next adjacent point was calculated and a speed was assigned using the time gap between the points. If the calculated speed exceeded 200 km/hr then the point was considered "scatter" and was excluded. This iterative process was repeated until most "scatter" points were excluded. Next, routes were excluded if the distance between any two adjacent points was more than 2 km with a time gap of more than 4 hours. The remaining routes were assessed individually and were eliminated either because >6 hours missing at beginning or end of route or because of large spatial daytime gaps. Routes with time-gaps in the night with a home-location were kept; assuming the subject simply stayed indoors at home for this period. For the final set of valid routes, points within 350 m of home and 400 m of work were identified as "at home" and "at work" respectively. The percentage of time at these locations based on the GPS route data was compared to the activity log data for this subset of participants.

For the remaining routes, time gaps were calculated between each GPS logged lat-long point. Subjects' home and work latitude and longitude were compared with each GPS route point and points within 350 m of home and 400 m of work were flagged respectively. All route points were plotted in ArcGIS and land-use regression values were extracted for every GPS route point using the "Extract Values to Points" tool.

A GPS Exact LUR estimate for each session with complete GPS route data was obtained by averaging the time-weighted LUR estimates for every GPS point in a route. A route estimate was calculated by the following formula where i is a point in time and $Poll_{xy}$ represents the pollution estimate at the spatial location of the gps point at that time.

$$Poll_{GPS} = \sum_{i=1}^{n} \left(\frac{(t_i - t_{i-1})}{\sum t_i} \times poll_{x_i y_i} \right)$$

A.2.2 Air Quality Monitoring Network Interpolation Models

A second exposure assessment model used in the Border Air Quality Study cohort analysis used the air quality monitors located throughout the Georgia Air Basin. For the purpose of this study, only the monitoring stations maintained by the GVRD were used. These monitoring stations are maintained by the regional district and use a variety of air monitoring equipment (Figure A.11. Data for September-December 2005 were obtained from the BC Ministry of the Environment web server and for January-September 2006 from the GVRD (personal communication Al Percival).

Since people don't live exactly at the location of the monitoring stations, the interpolation models must use some method to assign monitoring station values to people's address or postal code locations. In the BAQS study, five interpolation-type models were considered; two interpolation models were used in the final cohort analysis. The first model simply assigned values from the nearest monitoring station to the subjects' location. The second used an inverse distance weighted approach to combine the nearest 3 monitoring stations to the subject. A classic inverse distance weight calculation was used for the analysis (as was used in the BAQS study)3. The same two ambient monitoring station interpolation models that were used in the BAQS study are also used in this thesis: (1) Inverse Distance Weight of 3 Nearest Monitors and (2) Nearest Monitor.

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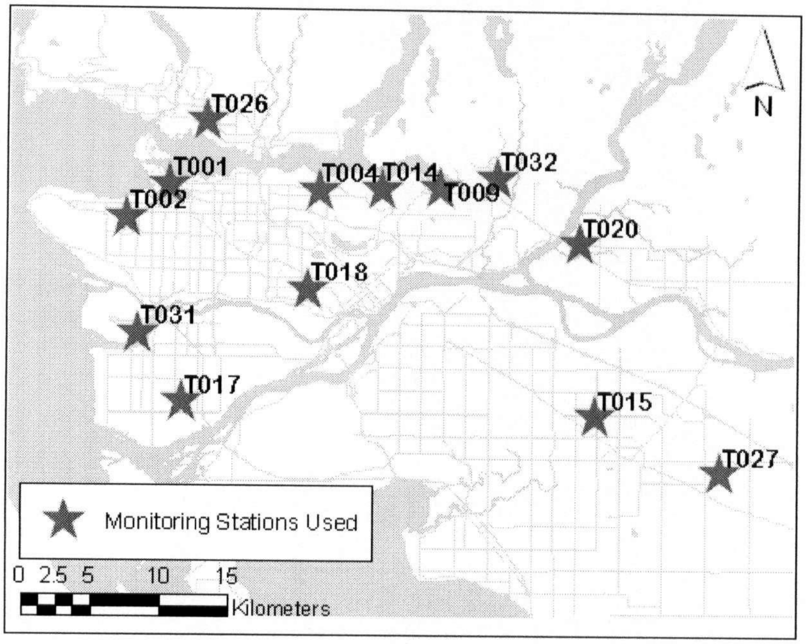
3 The inverse function defined as $F(x,y) = \sum_{i-1}^{n} w_i f_i$ and the weight function as: $w_i = \frac{h_i^{-p}}{\sum_{j-1}^{n} h_j^{-p}}$ where p=2.

Figure A.11 Ambient Monitoring Stations used in PHAIR Study



For the PHAIR Study, as with the BAQS cohort study, the ambient monitoring estimates were generated based on subjects' home postal codes and the distance from each postal code to the monitoring stations rather than for the participant home addresses.

The ambient monitoring data contains hourly measured concentrations at each station. Two exposure assessment methods were used to calculate the exposure estimate for the PHAIR study. The "time-specific" estimate obtained the start and end hours (rounded from the nearest half-hour) from the sampling session and averaged monitoring data from all hours in the sampling session. The "monthly" estimate was generated as a comparison to both the land-use regression model and cohort study analysis. Exposure estimates were calculated for all days in a 14 day window on either side of the sampling start and end dates. These estimates were then averaged to generate a "monthly" estimate centered on the sampling session.

References

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Appendix B Questionnaires, Sampling Forms, Protocols and Ethics Approval

Study Procedures:

- A technician will contact you to arrange an appointment to visit you at your home. At that time, he/she will equip you with a personal air pollution monitor and a small, quiet sampling pump (size 14 x 7.5 x 6 cm), to measure your personal level of air pollutant exposure (total weight 1.1 kg). When the monitor is worn (in a backpack), you may engage in all normal activities. When you are relaxing in one place or in bed, you may remove the sampler and allow it to operate without being attached to you. At the completion of the 48-hour monitoring period, the technician will retrieve the sampler and activity log (described below).

- You will be asked to wear the personal monitoring equipment on 3 occasions during your pregnancy (each 48 hours in length). The monitoring will take place approximately once per trimester, and sampling dates will be determined in collaboration with the research technician(s).

- A technician may also install an air quality monitor in a secure outdoor area at your residence and in an indoor location at your residence. This equipment will measure fine particulate matter ($PM_{2.5}$) in the air. The equipment is designed to operate quietly and unobtrusively and presents no known risks to the occupants of the home. The technician will also ask some questions about your home's characteristics (age, building material, etc.).

- You should engage in normal activities during the duration of the monitoring, and you will be asked to keep a simple log of any particle-generating activities nearby (cooking, dusting, smoking, barbequing, etc.) for this period.

- You will be asked to carry a credit-card sized (Global Positioning System) GPS-enabled data logger during each of the 48 hour monitoring periods. This will record information about your location during the sampling.

- You will be asked to complete a brief follow-up questionnaire after the birth. The air pollution level measurements recorded in this study will be used to analyze any possible relationship between birth outcomes and air pollution for a larger population study.

Exclusions:
Smoking will affect the results of this research, and therefore households with residents who smoke must be excluded from this study.

Risks and Discomfort:
There are no risks involved with the air pollution sampling. All sampling involves measurement of compounds normally present in outdoor and indoor air; no additional compounds will be added to the air as a result of the measurements. The GPS data logger does not emit any electromagnetic fields or radiation. The data logger is a receiver only and uses readily available sattelite signals to generate position data.

Wearing the sampler and pump may sometimes be awkward, but technicians will work with you to find a comfortable configuration. You will be trained to remove the sampler should the need arise. For example, when you are sleeping, the sampler should be placed at the bedside. In total, the sampling equipment weighs approximately 1.2 kg.

UBC Study on **P**regnancy, **H**ealth and **Air** Pollution
PHAIR Study

Participant Questionnaire

(Date: ______________)
(ID: ______________)

Participant Information

1 What is your age (on sampling day)? ______________________________

2 How would you describe your ethnicity/race (check all that apply)?

- ☐ White/Caucasian
- ☐ Chinese
- ☐ Other Asian
- ☐ Indian
- ☐ Native North American or Inuit/Northern Native
- ☐ Black or African
- ☐ Other

3 Estimated Due date: __________ ______________________________

4 How was due date determined?

- ☐ Doctor (last period date)
- ☐ Ultrasound
- ☐ Don't know
- ☐ Other? ______________________________

5 Single birth pregnancy?

- ☐ Yes
- ☐ No
- ☐ Don't know

6 How many other birth children do you have? ______________________________

7 Is there any smoking in your home? ______________________________

8 What level of education have you completed? (Please check degree/diploma received, if applicable)

- ☐ < Grade 9
- ☐ Grade 9 – 13 (high school)
  - ☐ With Graduation Certificate?
- ☐ Trades or Technical
  - ☐ With Diploma/certificate?
- ☐ College
  - ☐ With Diploma/certificate?
- ☐ University
  - ☐ With Diploma/Certificate?
  - ☐ With University Degree?
  - ☐ With Post-graduate Degree?

9 What is your approximate **family** annual income? (before taxes)

- ❑ < $20,000
- ❑ 20 – 40,000
- ❑ 40 – 60,000
- ❑ 60 – 80,000
- ❑ 80 – 100,000
- ❑ 100,000-150,000
- ❑ > 150,000

10 Do you currently rent or own your home (primary residence)?

- ❑ Own
- ❑ Rent

Employment Questions:

11 Are you currently employed (paid or volunteer)?

- ❑ Full Time
- ❑ Part Time
- ❑ Not working/Unemployed

12 What is the name of the company or organization you work for?

____

13 In which department do you work? ______________________________

14 What is your job title? ______________________________

15 Describe the primary industry of your company/organization (e.g. retail, tourism, engineering firm): ______________________________

____

Thank you for completing this questionnaire!

Would you be willing to be contacted after the birth to answer a very short questionnaire about the birth (e.g. date of delivery/weight/health) ?

- ❑ Yes
- ❑ No

UBC **P**regnancy, **H**ealth and **Air** Pollution – PHAIR Study

Dwelling Information Form

Section 1: Technician to Complete

Address and Location Information

[_ _ _ _]

1 Participant/Site ID: ______________________________

2 Date (when collected): ______________________________ [DDMMYYYY]

3 Address: ______________________________ [1=Van/Bby; 2=PoCo]

____

City: ______________________________
Postal Code: ______________________________

4 GPS Data (with secondary GPS) at Front Exterior Door of Residence:

Latitude: ______________________________
Longitude: ______________________________
Elevation: ______________________________
GPS Accuracy: ______________________________

Residence Data

5 Is this building located **on a major road** (major road = 4 lanes):

- ☐ Yes
- ☐ No

6 If No, is it **within 50m** of a major road?

- ☐ Yes
- ☐ No

7 What best describes the **type of building**/home this is?:

- ☐ A one-family house (detached from other houses)
- ☐ A one-family house attached to one or more houses
- ☐ Apartment building/townhouse with less than 4 apartments
- ☐ Apartment building with 5-9 apartments
- ☐ Apartment building with greater than 10 apartments
- ☐ Other: ______________________________

8 Is the building located in a **Street Canyon?**

(street where the ratio of the distance from the buildings to the axis of the street and the height of the building was less than 1.5)

- ❑ Yes
- ❑ No

Apartment location in building (if applicable):

9 Floor number: ______________________

10 Corner unit?

- ❑ Yes
- ❑ No

11 Side of building:

❑ North ❑ South ❑ East ❑ West

<u>Section 2: Complete during Interview with Study Participant</u>

Estimated home characteristics (Size and Age)

12 Square footage (approx): ______________________

13 Ceiling height (approx): ______________________

14 Number of rooms (in home): ______________________

15 Number of windows (in home): ______________________

16 Number of windows that open (percentage):

- ❑ None
- ❑ <25% (few)
- ❑ 25-75% (some; about half will open)
- ❑ >75% (mostly all open, 3 out of 4 or more)

17 Estimate percentage of floor space covered with carpets (for the entire house):

- ❑ No Carpets
- ❑ <25% (less than 1 in 4 rooms)
- ❑ 25-75% (some)
- ❑ >75% (mostly all carpeted)

18 What is the **age** of the building (years): ______________

Kitchen/Stove Information:

19 Does the kitchen have a **Gas stove**, cooking range or oven?

- ☐ Yes
- ☐ No
- ☐ Don't know

*if Yes, (**Have** a Gas Stove):*

a. Does the **gas stove** have a continuously burning Pilot Light?

- ☐ Yes
- ☐ No

20 Does the stove have a Ventilation/Range hood?

- ☐ Yes
- ☐ No

If yes (Have a ventilation/range hood)

a. How often is the Range Hood used?

- ☐ Always
- ☐ Often (at least ¾ of the time when cooking)
- ☐ Sometimes (more than ¼ of the time)
- ☐ Never

Ventilation in the Residence:

21 Does the house have an Air Conditioning system?

- ☐ Yes
- ☐ No

If yes, (Have Air Conditioning)

a. What kind of Air Conditioning?

- ☐ Window (in how many rooms?) ____________________
- ☐ Central
- ☐ Other ______________________________

22 If the home does not have air conditioning, what methods do the residents use to keep cool: ____________

- ☐ Open windows
- ☐ Ceiling fans
- ☐ Floor/table fans
- ☐ Other ______________________________

23 What type of Heating System (check all that apply)?

- ❑ Electrical
- ❑ Gas Furnace/Gas Fireplace
- ❑ Forced Air/Furnace
- ❑ Hot Water/Radiator
- ❑ Fireplace/Wood Stove
- ❑ Other:________

24 Does the house have a fireplace?

- ❑ Yes
- ❑ No

If yes, Have Fireplaces:

a. How many Wood Fireplaces? ____________________
b. How often is the Wood Fireplace used?____________________
c. How many Gas Fireplaces? ____________________
d. How often is the Gas Fireplace used?____________________

25 Does the house have an Independent air filter/cleaner (excluding furnace filter/air fresheners):

- ❑ Yes (See a-c)
- ❑ No

If yes, (Have air filter/cleaner):

a. What Type? ____________________
b. How often is it used? ____________________
c. Where is it located? ____________________

26 How often are windows opened for cooling purposes?

- ❑ Always
- ❑ Sometimes
- ❑ Never

27 How many windows in the house are generally open (when cooling needed)? ____________________

28 Total number of windows in the house? ________________

Other Questions

29 Does the house have an attached garage?

- ❑ Yes
- ❑ No

30 Does your family use/drive a car or other motor vehicle?

- ❑ Yes
- ❑ No

If Yes, (drive or use a vehicle) – For the vehicle ***primarily*** *used by the participant:*

a. What type of vehicle?
- ❑ Passenger Car
- ❑ Van
- ❑ SUV/Pickup Truck
- ❑ Motorcycle

b. What is the make/model of the vehicle? ____________________

c. What year is the vehicle? ____________________

31 Does your family have a **second** car or other motor vehicle?

- ❑ Yes
- ❑ No

If Yes, (drive a vehicle):

a. What type of vehicle?
- ❑ Passenger Car
- ❑ Van
- ❑ SUV/Pickup Truck
- ❑ Motorcycle

b. What is the make/model of the vehicle? ____________________

c. What year is the vehicle? ____________________

(Technician to Calculate)

32 Approximate volume (of home): ____________________

WORKPLACE Address and Location Information

33 Workplace Address: ______________________

____

City: ______________________
Postal Code: ______________________

Workplace Building Data

34 What is the estimated **age** of the building (years): ______

35 Is this workplace located **on a major road** (major road = 4 lanes):

- ❑ Yes
- ❑ No

36 If No, is it **within 50m** of a major road?

- ❑ Yes
- ❑ No

37 What best describes the **type of building** this is?:

- ❑ A one-family detached house
- ❑ A small retail or storefront
- ❑ Small multi-story (2-3 story) office building
- ❑ Open plan retail space (e.g. super market, big-box store)
- ❑ Mall complex (store)
- ❑ High rise office tower (>8 stories)
- ❑ Other: ______________________

38 Is the building located in a **Street Canyon?**

(street where the ratio of the distance from the buildings to the axis of the street and the height of the building was less than 1.5)

- ❑ Yes
- ❑ No

Work place location in building (if applicable):

39 Floor number: ______________________

40 Corner unit?

- ❑ Yes
- ❑ No

41 Side of building:

❑ North ❑ South ❑ East ❑ West

Estimated Size of Workplace:

42 Estimated square footage: ______________________

43 Ceiling height: ______________________

44 Approximate volume: ______________________

Workplace Ventilation and Exposures

45 Is there any smoking or particle sources at your workplace?

- ❑ Yes
- ❑ No

a. Particle sources at work? (describe) ______________________

- ❑ Cigarette smoking
- ❑ Cooking
- ❑ Vapours/Smokes ______________________

46 Type of Ventilation (natural or system?): ____________

47 Does the workplace have an Air Conditioning system?

- ❑ Yes
- ❑ No

If yes, (Have Air Conditioning)

a. What kind?

- ❑ Window (in how many rooms?) ______________________
- ❑ Central
- ❑ Other ______________________

48 If the workplace does not have air conditioning, what methods do people use to keep cool: ________________

- ❑ Open windows
- ❑ Ceiling fans
- ❑ Floor/table fans
- ❑ Other ________________________

49 What type of Heating System is used at your workplace (check all that apply)?

- ❑ Electrical
- ❑ Gas Furnace/Gas Fireplace
- ❑ Forced Air/Furnace
- ❑ Hot Water/Radiator
- ❑ Fireplace/Wood Stove
- ❑ Don't know

50 Does the workplace have an Independent air filter/cleaner (excluding furnace filter/air fresheners):

- ❑ Yes (see a-c)
- ❑ No

If yes, (Have air filter/cleaner):

a. What Type? ____________________
b. How often is it used? ____________________
c. Where is it located? ____________________

51 How often are windows opened for cooling purposes?

- ❑ Always
- ❑ Sometimes
- ❑ Never

52 How many windows are generally open? ______________

53 Estimated number of windows in the workplace? ______

54 Does the workplace have an underground garage?

- ❑ Yes
- ❑ No

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Filling in the activity log

It will probably be easiest for you to fill in blocks of time in the log a few times a day. Record your activity by circling the appropriate choice or drawing a line through a sequence of identical choices (e.g. at home all night).

For each half hour block of time:

1. Did you spend most of that period indoors, outdoors, or in transit?

   If **indoors**: record whether you were at home, at work, or somewhere else (other)
   If **outdoors**: record whether you were near home (on the property) or away
   If **in transit**: record whether you were traveling by car, bus/skytrain, walking, or other.
   If you were taking mass transit, record whether it was a diesel or electric bus, or a skytrain.

2. What was your activity level?
Lo: low activity level (e.g. sleeping, resting, sitting)
Mid: moderate activity level
Hi: high activity level (e.g. exercising, doing physical work)

3. Please indicate yes (y) or no (n) to the following:

Cooking: Were you cooking, or were you in the same room as someone cooking?

Tobacco smoke: Was someone near you smoking?

Windows open: Were there one or more windows open in the room you were in (if indoors)?

Wearing sampler: Were you carrying the bag on you? (i.e. circle N if sampler was on the couch next to you and Y if you are moving round with the bag on)

Notes: Please make a note if you did not have the sampler near you (for example, you accidentally left it at home when you went to the store; or you went to an exercise class and left it outside the room).

If you can, please note anything else unusual. For example, you were in a dusty or smoky place, or you noticed that the pump stopped.

Please phone us, if you can, if you notice the pump has stopped or if the blue light on the GPS stops flashing.

Pregnancy **H**ealth and **Air** Pollution (**PHAIR**) Research Study

Charging the GPS unit

The battery lasts for about 36 hours. Please charge the unit overnight either the first or second night (for at least 6 hours).

<u>You should not need to press the on/off button at any time</u>. Simply plug the unit into an outlet with the charger and then unplug in the morning.

The blue light should always be flashing (there may also be a green light when a signal is received or a red light for a low battery or when it is charging).

If there is no blue light, the unit has turned off. **If necessary, to turn unit on**: Press the button firmly. You will see the blue light flashing then the green light will flash once. Release the button as the green light flashes off. The blue light should continue flashing. This may take a couple tries!

Person ID:____ Start Date:_________ Time:_________ Stop Date:_________ Time:_________ Data Entered:____
Filter: ST-_____

Time	Indoors			Outdoors		Transit (D=Diesel Bus, E=Electric Bus, ST=Sky Train)						Activity Level	Cooking	Tobacco Smoke	Windows Open	Wearing Sampler	Notes
	Home	*Work*	*Other*	*Near Home*	*Away from Home*	*Car*	*Bus*	*Bus Type*	*Walk*	*Other*	*# minutes*	*Lo Mid Hi*	*Y N*	*Y N*	*Y N*	*Y N*	
8:00-8:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
8:30-9:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
9:00-9:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
9:30-10:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
10:00-10:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
10:30-11:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
11:00-11:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
11:30-12:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
12:00-12:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
12:30-1:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
1:00-1:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
1:30-2:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
2:00-2:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
2:30-3:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
3:00-3:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
3:30-4:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
4:00-4:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
4:30-5:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
5:00-5:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
5:30-6:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
6:00-6:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
6:30-7:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
7:00-7:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
7:30-8:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	

Time	Indoors Home	Indoors Work	Indoors Other	Outdoors Near Home	Outdoors Away from Home	Transit (D=Diesel Bus, E=Electric Bus, ST=Sky Train) Car	Bus	Bus Type	Walk	Other	# minutes	Activity Level Lo Mid Hi	Cooking Y N	Tobacco Smoke Y N	Windows Open Y N	Wearing Sampler Y N	Notes
8:00-8:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
8:30-9:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
9:00-9:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
9:30-10:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
10:00-10:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
10:30-11:00 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
11:00-11:30 PM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
11:30-12:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
12:00-12:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
12:30-1:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
1:00-1:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
1:30-2:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
2:00-2:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
2:30-3:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
3:00-3:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
3:30-4:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
4:00-4:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
4:30-5:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
5:00-5:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
5:30-6:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
6:00-6:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
6:30-7:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
7:00-7:30 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	
7:30-8:00 AM	Home	Work	Other	Near	Away	Car	Bus	D E ST	Walk	Other		Lo Mid Hi	Y N	Y N	Y N	Y N	

What was your primary mode of transit (on this day)? Car Bus Walk Other

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Participant Post-Birth Questionnaire

(Date: ______________)
(ID: ______________)

Participant Information

1 What was the date of the birth? ______________________________

2 Multiple births?

- ❑ 1 Gender? ___________
- ❑ 2 Gender? ___________
- ❑ >2 Gender? ___________

3 Baby weight at birth (if multiple births, please list)? ______________________

4 Baby length at birth? ______________________________

We should be able to figure out gestational age based on due date

5 Were there any complications during pregnancy? (describe)

____

____

____

6 Were there any complications during the birth? (describe)

____

____

____

7 Does the baby have any known health concerns? ______________________

____

____

8 Was there any smoking in the home during your pregnancy? ____________

9 Did you consume alcohol/drugs during pregnancy? ______________________

Thank you for completing this questionnaire!

Start date:____________________ End date:_____________________

Study Participant:

Name:	Sampling Session: ❑ First ❑ Second ❑ Third	ID:

Forms, Questionnaires and Explanations:

If first visit:	If second/third visit:
❑ Consent form completed (give copy) ❑ Participant questionnaire completed ❑ Dwelling information sheet completed ❑ Activity log explained and demonstrated ❑ Contact information card given ❑ Confirmed end time appointment ___ ❑ Discuss keeping sampler near them ❑ Discuss potential problems: tube coming out, flow impeded, pump stopping	❑ Did they move? (complete new dwelling info) ❑ Did their workplace change (new dwelling info) ❑ Activity log explained and demonstrated ❑ Contact information card given ❑ Confirmed end time appointment ___ ❑ Discuss keeping sampler near them as much as possible (e.g. night-time; swimming) ❑ Discuss potential problems: tube coming out, flow impeded, pump stopping

NOx Sampling:

Ogawa NOx Sampler ID:	Start time (opened)	End time (closed, put away)
	Comments:	Time elapsed (mins):

PM Sampling:

- ❑ Before session - Pump flow rate calibrated (5.00 L/min)? Adjustment:______________
- ❑ After session - Pump flow rate checked? Flow: ___________
- ❑ After session - Sampler disassembled from pump and put in Ziploc bag

Pump ID:	PEM Filter ID:	Pump Start Time:	Pump Off Time:
		Comments:	Time elapsed (mins) : Volume sampled (L):

GPS Sampling:

- ❑ Confirmed first reading outdoors?

Blue Logger ID:	Start time (turned on):	End time (turned off):
	Comments:	Comments:

Post-session questions to ask participants:

- ❑ Did you have any problems with the equipment?
- ❑ Where did you leave the pump at night?
- ❑ Check activity log is filled out correctly. Query anything unusual.

- ❑ Make next sampling appointment (unless this is the last) ________________
- ❑ If last session, say we'll be in touch 4-6 weeks after due date for post-birth questionnaire
  - o Confirm contact info (generally home phone number)

Post session lab activities:

Activity (immediately)	**Date**	**By whom**
GPS Data Downloaded File: ________________		
NOX sampler stored in fridge		
PM filter put in Petri dish in environment room		
Check pump history: verify volume ________________		

Activity	**Date**	**By whom**
NOX filters extracted with water in vial, stored in fridge		
PM filter weighed		
PM filter absorbance measured		

Data Entry	**Date**	**By whom**
Sampling session - PHAIR_SubjectsAddrSampleID.xls - Subjects (date); Sample summary; Locations (home +work)		
PM filters – PHAIR PM FILTER weights.xls - mg per m3 calc; volume correction		
NOx filters - PHAIR NOX filter data.xls - time elapsed (may differ from pump!)		
Activity Log data		
Q1 – Participant Info Data		
Q2 – Dwelling Info		

Additional comments:

Environmental Conditions:

Environmental Conditions	Temp (day, night)	Humidity (RH %)	Weather conditions, notes
Day 1			
Day 2			

Pregnancy Health and Air Pollution (PHAIR) Study

Pre-sampling preparations

PM2.5 Sampling

- ❑ Filters pre-weighed
- ❑ Field and lab blanks prepared as necessary
- ❑ Clean sampler parts assembled, leak tested (allow 2 days to clean and dry samplers)
- ❑ Sampler assembled with sample filter and oil drops added
- ❑ Pump battery fully charged
- ❑ Pump set to 5 L/ min

NOx sampling

- ❑ Clean samplers assembled with NOx and NO2 filters and labeled
- ❑ Check use by dates

GPS loggers

- ❑ Battery fully charged (charge with unit on for a few hours to ensure internal battery is also charged)
- ❑ Clear memory log
- ❑ Set logging to every 5 seconds, enable logging and send settings to logger
- ❑ On sampling day: go outside and get satellite signal, ensure data is being logged
- ❑ Get satellite signal at participants home (or en route).

Learn More

Researchers at UBC are investigating how much air pollution women in the Vancouver area are exposed to during pregnancy. If you would like to learn more about the study, please contact the study team. They would be happy to discuss it with you.

Elizabeth Nethery, MSc Student
[redacted]
Sara Leckie, Research Scientist
[redacted]
www.cher.ubc.ca/phair

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photo: earthsound

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Health Canada Santé Canada

BC Centre for Disease Control

Pregnancy, Health and Air Pollution

Help us learn about the effects of air pollution on health by participating in a UBC research project.

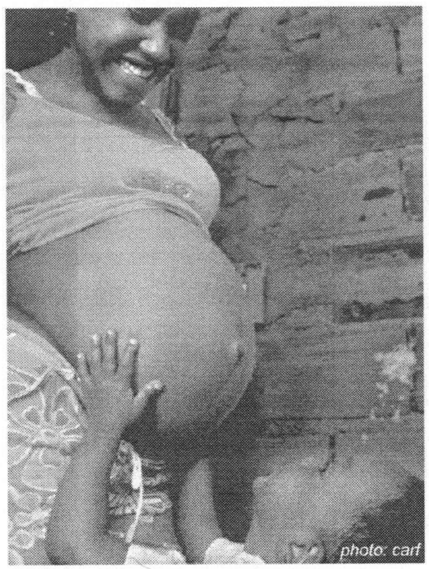


photo: carf

Air pollution can affect your health and the health of your baby. Find out what you can do about it.

UBC

CHER

Are You Pregnant?

Are you interested in air pollution and its effects on your health?

If so, you might be interested in participating in a UBC research study on pregnancy, health and air pollution.

What is the Purpose of the Study?

We want to better understand the amount of air pollution women encounter in their daily lives. This information will help to better understand the health effects of air pollution for pregnant women.

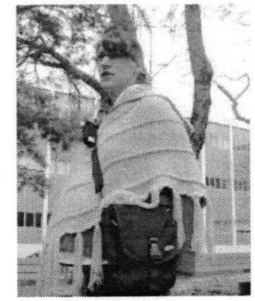
Who Can Participate?

We are asking for participation from women in their first or second trimester who live in the Greater Vancouver Regional District.

What Would I Need to Do?

Your participation would involve:

- wearing an air sampler and GPS data logger on 2 or 3 occasions, for 48 hours
- keeping a brief log of your activities during this time
- completing a brief questionnaire about yourself and your home and work environment
- completing a brief post-birth questionnaire



The personal sampling equipment worn by volunteers weighs about 1kg and fits into a small shoulder bag or knapsack.

Do I Have to Travel to UBC?

No. We will visit you at your home to begin and end the sampling sessions.

How Will My Confidentiality Be Protected?

All personal information and data collected will remain confidential and we will not store information about you or your home beyond the study period.

Will I Be Informed of the Study Results?

We will provide all volunteers with a summary of their own measurements, as well as a summary of overall project findings.

If you would like more information about participating in this study, please call (604) 822-1274, or visit us online at www.cher.ubc.ca/phair.

Pregnancy, Health and Air Pollution: What You Should Know

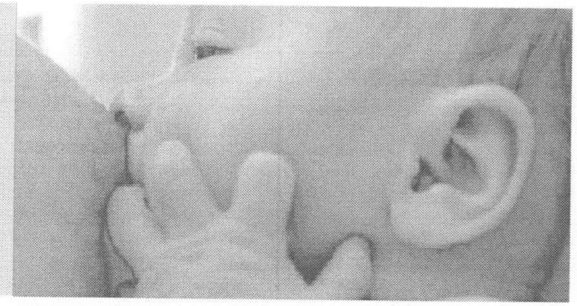
Poor air quality can harm your health, and if you're pregnant, it may affect the health of your baby. All people living in the Vancouver area are exposed to some level of polluted air in their daily lives, whether it is commuting to work, exercising outside, or even carrying out common household tasks.

What do we know about air pollution and pregnancy?

Recent research studies suggest that babies who are exposed to higher levels of urban air pollution when they are in the womb are more likely to have health problems. The health problems that have been linked to air pollution include:

- Pre-term birth: A baby born more than three weeks before his or her due date.
- Low birth weight: This results from either a baby born too early (see above) or due to poor growth of the baby during pregnancy

Babies born pre-term or with low birthweight are more likely to have health problems after they are born.



Sources and Types of Air Pollution

Air both outside and inside of our homes can be a source of pollution and irritants. Below are lists of some of the most common indoor and outdoor air pollutants:

Outdoor

- Traffic emissions are an important source of harmful pollutants such as carbon monoxide, particulate matter (see below) and smog.
- Wood smoke from fireplaces or forest fires pollutes the air.
- Particulate matter (PM), which includes tiny particles such as dust, dirt, soot and smoke, is thought to be one of the most important components of outdoor air pollution that can cause health problems.

Indoor

- Tobacco smoke
- Paints, glues, air fresheners, cosmetics, pesticides, and other common household products
- Water-damaged materials and moulds
- Unvented gas appliances such as space heaters, gas fireplaces and gas stoves
- Dust containing pet and dust mite allergens

Air Quality in the Greater Vancouver Area

Air quality in our region is good and usually falls within acceptable levels. However, factors like traffic, industrial and commercial activity, as well as our region's geography and weather conditions can contribute to the difficulties we face in ensuring clean air.

What Can I Do?

- Don't smoke, and avoid the smoke of others. Tobacco smoke exposure during pregnancy has a strong influence on the health of babies.
- Reduce the time you spend in high traffic areas.
- Do your part to reduce air pollution by taking public transportation, walking, and choosing fuel-efficient vehicles.
- Avoid using potentially dangerous products such as paints or air fresheners. Substitute with low emission products and use in well-ventilated areas.
- Identify key sources of air pollutants at home and/or work and take steps to rectify them.
- On the few days when air quality is poor, avoid or limit exercising and spending time outdoors.

Helpful Resources and Links

UBC Pregnancy, Health and Air Pollution Study:
www.cher.ubc.ca/phair/

BC Lung Association:
www.bc.lung.ca/
Find local resources and air quality reports

BC Healthfiles:
www.bchealthguide.org/healthfiles/
For information on air quality and pollution

GVRD Air Quality:
www.gvrd.bc.ca/air/
For information on our region's activities around monitoring and controlling air quality

The Movement for Clean Air Now:
www.lung.ca/cando
Contains helpful hints for improving the air quality in and around your home and workplace

Environment Canada:
www.ec.gc.ca
Clean Air online section has resources to help Canadians make informed decisions and take action to reduce air pollution

Health Canada Air Quality information: www.hc-sc.gc.ca/ewh-semt/air/index_e.html
Provides information about Canadian research and regulations covering air quality

Sampling Protocol Overview
PHAIR Study, UBC

Paperwork:

Follow Sample Log sheet to ensure all paperwork and instructions are given and required information is recorded.

First session start:

- ❑ Ask participant to read and sign consent form (1 copy to participant, 1 signed copy kept by researchers)
- ❑ Ask participant to complete Participant Questionnaire
- ❑ Complete Dwelling Information Questionnaire with participant
- ❑ Explain activity log to participant and give to her (along with instruction sheet)
- ❑ Give participant contact info sheet
- ❑ Confirm end-time appointment (and place) – should be 48 hours ±3 hours from start-time.
- ❑ Discuss: keeping sampler near them at all times (e.g. night-time, swimming, quiet meeting)
- ❑ Once equipment is set up and turned on, discuss potential (rare) problems: tube coming out of pump, flow rate being impeded, pump stopping
- ❑ Thank participant!

Second or third session start:

- ❑ If participant has moved (within study area) or their workplace has changed, complete another Dwelling Information Questionnaire
- ❑ Go over activity log again briefly and give her log, instruction sheet and contact info sheet
- ❑ Confirm end-time appointment (and place) – should be 48 hours ±3 hours from start-time.
- ❑ Remind re: keeping sampler near, and potential equipment problems
- ❑ Thank participant!

End of sessions:

- ❑ Ask whether there were any problems with the equipment and record.
- ❑ Ask whether sampler was in their bedroom at night and record
- ❑ Go through activity log with participant and ask for clarification if necessary
- ❑ Suggest approximate dates for next sampling session (if applicable) and either set a tentative time and date or arrange to call/email closer to the time.
- ❑ If final sampling session, let her know we'll be in touch 4-6 weeks after due date for post-birth questionnaire (and gift). Verify home phone number contact (or email if preferred)
- ❑ Thank participant!

Sampling Equipment

Refer to detailed SOPs for Filter Weighing, PM2.5 samplers, Leland Legacy Pumps, Ogawa samplers, GPS data logging, Filter Absorbance Measurements.

PM2.5 Sampling:

Equipment to bring for sampling:

- ❑ SKC Leland Legacy Pump (+1 extra)
- ❑ Noise case for pump
- ❑ Loaded sampler (+1 extra and field blanks as required)
- ❑ Dry Cal
- ❑ Calibration head
- ❑ Screwdriver
- ❑ Tubing and adaptors
- ❑ Aluminum shield for sampler
- ❑ Bags (2-4 of various types so participant can choose)

In lab prior:

- ❑ Pre-weigh filters
- ❑ Clean samplers and allow to air-dry 24-48 hours
- ❑ Leak-test, load filter, and apply oil to samplers prior to use (can be a few days before); store in individual clean, labeled Ziploc bag

On-site prior:

- ❑ Calibrate pump prior to beginning sampling. Clear history at this time so that session starts with 0 min and 0 L.
- ❑ Have participant select bag and verify that tubing length is good for them (tubing should come out of bag and over shoulder so than sampler and shield rest in front of their shoulder)
- ❑ Turn pump on and record start time (from pump clock). Put pump in noise case and into bag.

On-site post:

- ❑ At end of session, Turn pump off and record stop time (from pump clock). Record elapsed time (min) and volume (L).
- ❑ Check pump calibration and record average flow rate from Dry-Cal
- ❑ Put PM2.5 sampler in clean Ziploc bag to return to SOEH

In-lab post:

- ❑ Disassemble sampler and put filter into Petri plate and into weighing room
- ❑ Check pump history to verify time/volume of sample, whether pump stopped (and cause)
- ❑ Charge pump battery for next session

NOx sampling (Ogawas)

Equipment to bring for sampling:

- o Loaded Sampler (+1 extra)
- o Clip (+ extras) to secure sampler to outside of bag

In lab prior:

- Clean samplers and allow to air-dry 24-48 hours
- Load samplers – do a batch of about 20 (depending on sampling schedule).
- Store loaded samplers in ziploc bag and orange vial in refrigerator. NOTE: Samplers must be used within 90 days once loaded

On-site prior:

- At start of sampling session, remove Ogawa sampler from vial and Ziploc and attach to outside of bag using clip. Record start time (from pump clock).

On-site post:

- At end of session, replace Ogawa sampler into Ziploc and orange vial. Record stop time (from pump clock).

In-lab post:

- Add a label stating that sampler has been exposed and the date. Store in fridge for a maximum of 15 days before extracting filters in water.

Equipment needed:

- Loaded Sampler (+1 extra)
- Clip (+ extras) to secure sampler to outside of bag

<u>GPS data logging</u>

Equipment to bring sampling:

- DeLorme Earthmate Blue Logger GPS (+1 extra) setup in Alti-tech case with external battery
- USB Bluetooth key for checking settings at SOEH or at sampling site

In lab prior:

- Ensure logger battery is fully charged (min. 8 hours)
    - Ensure logger has been charged (8 hours) with power ON within last 4 days
- Verify logger settings and that logging is enabled
- Verify satellite signal reception and data logging at SOEH on day of, or prior to, sampling

On-site prior:

- Turn logger on outside participant's home (or en route), and verify satellite signal reception. Record approximate start time.
- Put logger into bag with pump so that charger connection is facing down and flashing LEDs are facing outside of bag (this is to increase logger's ability to receive signals).

On-site post:

- At end of session, turn unit off. Record approximate stop time.

In-lab post:

- Download GPS data
    - ensure Daylight Savings Time = OFF; units = metric; lat/long format = degrees
- Open file in Excel and check data coverage over 48 hours against the activity log
- Clear logger memory
- Charge GPS logger battery to prepare for next use (can be stored plugged in)

SOP- Leland Legacy Pumps and Calibration
PHAIR Study, UBC
Sept 2005

Field Procedures: Leland Legacy Pump

- Verify that there are no automatic sampling programs or schedules on the pump.

Calibrating Pump flow rate (onsite prior to start of session):

(Note – if Dry-Cal is cold (e.g. left in car overnight), the readings appear to be inaccurate)

- Attach PM2.5 sampler to pump using tubing
- Place calibration cap over sampler and attach to Outlet port of Dry-Cal with tubing
- Start pump and enter setup mode
- Verify flow rate is set to 5.00 L / min
- Press * to go to flow adjustment screen
- Turn on Dry-Cal. Press and hold Read button (for auto read)
- Use the average of 10 readings on Dry-Cal to determine flow rate
- Press ▲ or ▼ key as necessary to adjust flow to 5.00 average reading on Dry-Cal (you may need to wait a minute or two for readings to stabilize)
- Press * until you see CLR, then press the ▲ and ▼ keys down simultaneously (to clear history).
- Press * until you see END, then press the ▲ and ▼ keys down simultaneously (to saving settings and calibration).

Checking flow rate (on site at end of session):

- Make sure session time (min) and volume (L) is recorded after turning pump off and before checking calibration!
- Setup sampler, pump and DryCal as above
- Start pump
- Turn on Dry-Cal. Press and hold Read button (for auto read)
- Use the average of 10 readings on Dry-Cal to determine flow rate. Record this value on sample log sheet.
- Stop pump and turn off.

Checking pump history:

- Back at SOEH, look at pump history using computer software interface
- Check for any problems such as pump turning off due to faults etc.
- You can also verify by calculating the number of minutes from start time to end time and checking that this matches the time elapsed and volume recorded at the end of the session.
- NOTE: Occasionally, there seems to be errors with the pump history (e.g. the history will indicate a pump was in HOLD mode when, in fact, it was running!).

Standard Operating Procedures: Leland Legacy Pump (LLP)

Powering the pump ON

- press the * button

Powering the pump OFF

- press the * button, hold until OFF 3 appears on the screen. Pump will countdown from 3 seconds and subsequently turn off. Pump will automatically turn off after a few minutes in HOLD mode.

Start/Stop Pump Operation

- START: Press & hold the ▲ and ▼ keys down simultaneously until the 'HOLD' disappears from the screen – you will subsequently hear the pump start to draw air
- STOP: Press & hold the ▲ and ▼ keys down simultaneously until the 'HOLD' reappears from the screen – you will subsequently hear the pump cease drawing air

Changing Pump Setup Options

- Press the following button sequence: * ▲ ▼ * . The word SETUP will appear on the screen.
- Press the * to scroll through the various setup options, which are:
    1. Pump flow rate
    2. Calibration adjustment for pump flow rate
    3. Time/date clock
    4. Temperature units
    5. Pressure units
    6. (Program shutoff)†
    7. clear pump history
    8. end setup

Protocol for DeLorme Earthmate BlueLogger GPS units

PHAIR Study, UBC
2005-2006

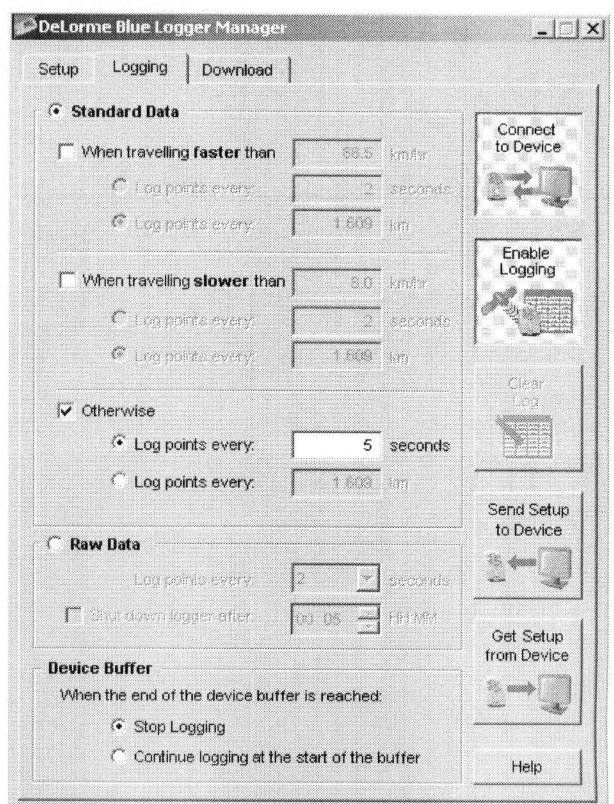
Setting up the GPS Blue Loggers

Note: Bluetooth connection procedure seems to vary among computers and operating systems! There are more difficulties with Windows XP than Windows 20000.
Some troubleshooting may be required!

1. Establish Bluetooth connection
   - right-click on the Bluetooth device in bottom left (taskbar)
   - Select Quick Connect -> Bluetooth Serial Port -> Earthmate BlueLogger GPS
   - Wait for message (connect to serial..) and taskbar bluelogger logo should go green in the middle and blue light on logger should be ON (not flashing).
   - Open BlueLogger Manager
   - Click on "Connect to Device" (you may need to select the appropriate COM port)

2. Set unit to log data
   - Ensure memory ("buffer") is empty - Click on Clear Log to delete old data
   - Click on Enable Logging
   - Adjust Logging settings as needed: Standard data, "otherwise", every 5 seconds. (see screenshot)
   - Click Send Setup to Device; wait for confirmation ("Bluetooth logger has received the settings")
   - Click on top "Connect to Device" to close the Bluetooth connection. Check that blue light on logger is now flashing.

3. Verify unit is logging data
   - It is generally a good idea to go outside and get a satellite signal (wait for green light on logger to flash).
   - Re-establish Bluetooth connection and verify on Set-up screen that data points have been logged (memory should have been cleared in preceding steps).



Downloading points from Bluelogger:

1. Turn logger on (or plug into cradle to charge) and then turn on (same process as above).
2. Connect to logger with Blue logger manager (same as when setting up the logger)
3. Verify Time Zone is Pacific Time and **<u>Daylight Savings Time is checked off.</u>**
4. Lat/Long should be selected as degrees (must be decimal degrees for ArcGIS)
5. Click on Download Tab
6. Select download all points
7. Click on "Get data from Device"
8. Save data as a Text file with the date of sampling, blueloggerID and Subject ID in the following format:
    a. YY-MM-DD LOG ## PH###.txt
9. Open file to verify data are downloaded and saved.
10. Clear log so it is ready for next use.
11. Charge battery so unit is ready for next use.

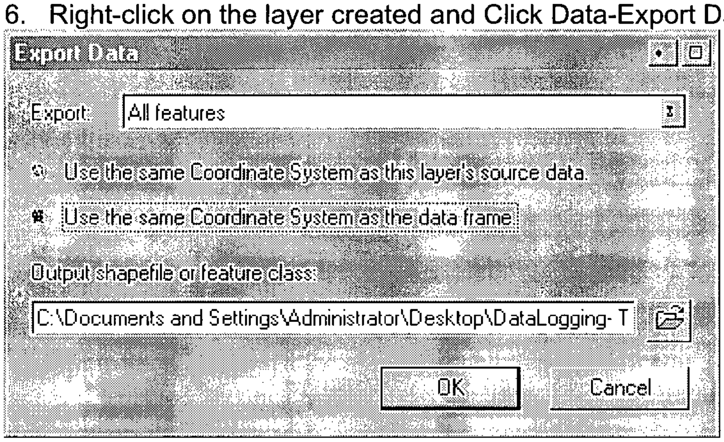
<u>Import data into ArcGIS:</u>

Step 1 – Convert Text to DBF File in Excel:

1. Open Text file from logger in Excel (convert to columns using comma and space delimiters)
2. Widen columns so that all characters are visible
3. To preserve decimal places, format cells as Numbers and specify correct number of decimal places
4. Watch you don't lose precision in Lat-Long (10 character max. for header and data)
5. Delete extra columns you don't need.
6. Save as DBF File

Step 2 – Import as layer in ARC

1. Run ArcMap
2. Open appropriate Clipped Background/Roads file
3. Select Tools – Add XY Data
4. Browse to DBF file created
5. Select X Field as Longitude and Y field as Latitude
6. Right-click on the layer created and Click Data-Export Data



    a. Save the exported data in a location with the appropriate naming, Click OK
    b. Say "yes" to add the exported data as a shape file
    c. Remove the DBF layer.

d. Change the layer settings to display by speed, heading, as needed.

Using BlueLogger GPS units with Alti-tech battery cases

1. Make sure logger is fully charged before use – plug in with charger for a minimum of 8 hours (can be kept plugged in between uses). There is no way to verify that the battery is fully charged. Periodically, leave unit charging with power on to ensure that logger's small internal battery does not become drained.
2. **TO TURN LOGGER ON:** Hold down button until green light goes on and then release as soon as green light goes OFF (2-4 seconds). If you wait too long, logger will turn off, not on. Blue light should continue to flash and green light will be off until a GPS signal is established.
3. Using Bluetooth connection to computer (or PDA), verify that log is cleared, logging is enabled, and settings are correct.
4. It is preferable to get a satellite signal (green satellite LED flashing) and verify that the data are actually being logged (this will involve going outside to get a signal if you are at SOEH).
5. Ensure the logger is receiving satellite signals before entering participant's home.
6. Battery is low when Bluetooth light starts flashing red. Battery should technically last 60 hours (at least 48 hours), but low battery light is sometimes flashing at the end of a 48-hour session.

Filter weighing, cleaning, assembling, and leak-testing PM samplers
Sampling Protocol

PHAIR Study, UBC
May 9, 2006

SOP (PRE and POST) Weighing of filters:

(pre-weighing can be done at any time before sampling)
(post-weighing can be done at any time after sampling)
(store new or used filters in weighing room (min. 48 hours) to allow them to equilibrate)

Note: Always have at least 5 pre-weighed filters to avoid running short for sampling!

Equipment:

- Teflo w/ring 37mm membrane – Pall Part# 22PJO37 – CA28139-109 (50/pack)
- Clean petri dishes
- Forceps and tweezers
- kimwipes
- labels and non-smudge pen (need to peel off)
- filter weighing log sheets
- Control Filters (on shelf in weighing room)

Procedure:

Preparation:

- Store filters (new or used) 48 hours in Environment Room before weighing (should be within appropriate temperature and relative humidity range)
- Weigh 3 gravimetric control filters *before* and re-weigh at least 1 filter *after* each weighing session
  - Record weights in Control QC spreadsheet
  - Check that control filter weights are within 2 standard deviations of the mean of all prior measurements (for each filter)
- Label petri dish two times ie. EN-101 to EN-315

Weighing:

- Tare balance
- Using tweezers, pass filter between electrostatic reduction plates a few times
- Smoothly open the balance lid, carefully place filter in centre of pan and close lid
- Once stability circle appears on balance display, record weight on sheet
- Remove filter and allow balance to return to zero. Tare if necessary.
- Weigh each filter three times (ensuring balance is at zero between weights and filter is passed between electrostatic reduction plates).
- If repeat weights differ by more than 0.01, restart.

  For example,

  102.112 to 102.122 ok

  102.112 to 102.130 not ok

  This must be true among all three weights

- Place weighed filter in labeled Petri-dish.
- Record date, temperature, RH, and 3 weights on filter weighing log sheet
- Store UNUSED (blank) pre-weighed filters on shelf in weighing room (Label shelf).
- Store post-weighed (USED) filters on shelf after sampling, prior to reflectance measurements.

SOP - Deep Cleaning Samplers:

- Do at least 3 days before using sampler.
- Requires at least 1-2 days for sampler to dry completely after cleaning.
- Make sure sampler has an O-ring before and after cleaning
- Can clean a batch of samplers at one time.
- Do cleaning in the AQ Lab; run sonicator in lab or in Main Lab

Equipment:

- kimwipes
- cafeteria trays (line with kimwipes and let things air dry on them)
- all sampler parts
- dishsoap (nonabrasive soap to clean samplers)
- big beakers (put all small parts in to soak)
- distilled water in small squirt bottles and/or large container
- sonicator

Procedure:

- line cafeteria trays with kimwipes – place to the right of the sink in the AQ lab
- separate sampler parts into large beakers with (1-2 drops of soap) and distilled water

Samplers (EXCEPT Impactor plates):

- let soak 15mins
- rinse 3 times with distilled water
- lay out sampler parts on trays (with kimwipes) and cover with kimwipes to prevent contamination while drying

Impactor Plates:

- carefully remove visible particles with razor blade
- sonicate for 15-30 mins in beaker with soapy distilled water (1-2 drops of soap)
- rinse 3 times with distilled water
- lay out impactor plates on trays (with kimwipes) and cover with kimwipes to prevent contamination while drying

After cleaning:

- Store cleaned samplers in labeled Ziplocs on shelf in AQ Lab. Label bag "CLEANED – Initials – DATE".
- Store in bags with components sorted (screens, tops, plates, etc)

SOP - PEM (PM2.5) Sampler Assembly:

- **At least 1 day before sampling**
- Store loaded sampler head in Ziploc bag in AQ Lab with equipment
- Do not load samplers more than 1 week prior to use.

Equipment:

- cafeteria trays (optional)
- kimwipes
- clean sampler components (including o-rings, bases, screens, impactor plates, inlets, screws)
- screwdriver
- pre-weighed filters
- forceps, tweezers
- Ziploc bags

Procedure:

- transfer the required # of pre-weighed filters from the weighing room to the lab
  - for every 20 samples, set one pre-weighed filter aside as a lab blank
  - for every 10 samples, take an extra pre-weighed filter to be used as a field blank (load into sampler, carry to site, return and weigh filter as usual)
- use PM filter log to record anything that happens to filters
- line tray with kimwipes
- assemble in the following order (ascending):
  - base
  - screen
  - pre-weighed filter (use forceps to transfer from petri dish to screen)
  - impactor plate (oiled with ~5 drops of impactor/mineral oil)
  - inlet with o-ring – OR use o-ring already glued into sampler
- tighten sampler with 2 screws
- transfer 2 petri dish labels from petri dish to bottom of sampler
  - (any assembled sampler with two labels is unused)
- Proceed to LEAK TESTING

SOP - Leak Testing:

(done the day before sampling, right after assembly)
(all samplers at once)

Equipment:

- leak test pump
- rotameter
- assembled samplers
- tubing
- calibration cap

Procedure:

- hook up:

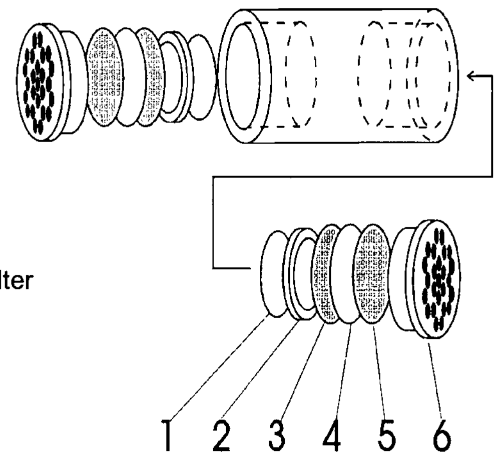
pump ← rotameter ← sampler (with calibration cap on it)

(← = direction of air flow)

- start pumping running
- put thumb over the end of the calibration cap nozzle
    - if rotameter reading goes near zero (<10 units), no leak
    - if rotameter reading stays high, leak
- if no leak, OK, move on
- if leak, try to fix it (disassemble sampler)
    - check that screws have been tightened properly
    - o-ring in sampler inlet may be askew
    - filter may be placed wrong
    - try a different base with a different inlet, some fit together better than others
    - try regluing o-rings (last resort)
- put samplers in individual Ziploc bags, ready for sampling

Field Procedures, Ogawa Passive Samplers (NO_x and NO_2)
PHAIR Study, UBC
2005

By Elizabeth Nethery, modified by Sara Leckie



1 Solid Pad
2 Pad Retaining Ring
3 Stainless Screen
4 Coated Collection Filter
5 Stainless Screen
6 Diffuser End Cap

<u>Washing and Cleaning Ogawa Samplers</u>:

- Clean hands.
- Sort sampler parts into groups (ie. Solid pads, retaining rings, screens, sampler tubes, end caps)
- Place the sampler parts into beakers of distilled water. Place beakers in the ultrasonic cleaner (with approx 1-2" of water in the basin) and run cleaner for about 15 minutes. Rinse each beaker's contents three times with distilled water.
- Lay out large Kim-wipes on cafeteria trays and arrange samplers components to dry on the trays (in groups). Use tweezers (or clean hands) to lay sampler parts on trays.
- Cover sampler components with Kim-wipe to keep clean while drying
- Wait until dry – 24-48 hours.
- Bag all sampler components into Ziplocs in groups (ie. All Solid pads, etc..) and label "Ogawa Solid Pads, CLEANED, Date-cleaned, Initials".

<u>Assembly and Loading of NOx/NO2 samplers:</u>

NOTE: Shelf life of sampler after assembled and stored in bag, in plastic vial is <u>90 days</u> (Refrigerated).

- Remove (1 vial each) NOx and NO2 vials from FREEZER at least 2-3 hours prior to using and let filters come to room temperature before loading samplers (to avoid condensation on the filters)
- Ensure no NOx contamination in area when loading samplers
- Locate:
    - bags of cleaned sampler components
        - Screens (4 per sampler)
        - Retaining Rings (2)
        - Solid Pads (2)
        - Sampler Tubes (1)
        - Diffusion Caps (2)
    - orange vials (plastic storage containers, opaque)
    - label materials (prepare 2 labels per ID)
    - Ziploc bags for inside orange vials.
- Set up a clean area with Kim-wipes laid out and Organize sampler parts

- Lay out sampler tubes (e.g. 10)
- Label sampler tubes with one set of labels, and orange vials with second set of labels
- Load both ends of each tube with:
    - a solid pad (use tweezers)
    - a retaining ring (use tweezers)
- For next steps, it is easiest to do sets of about 5 samplers, to minimize filter exposure.
- Load one end of each tube with:
    - a screen (use tweezers)
    - a NOx filter (use tweezers)
    - a screen (use tweezers)
    - a diffusion cap (use hands)
- TURN sampler tubes over and repeat screen and filter loading process for other side of the sampler using a NO_2 filter.
- Bag each sampler in a Ziploc bag and place inside correctly labeled plastic vial
- Note on sample sheet all vials loaded and date when they were loaded. Add note "USE BY .. 90 days from sample load date".
- Place labeled vials in refrigerator.

Using Samplers

Day of sampling:

- Remove samplers from refrigerator and transport (in orange vial) to sampling location.
- Record Start time and date on log sheet (use start and end time from pump display)
- Remove plastic bag and sampler from vial. Remove sampler from plastic bag and store plastic bag in vial.
- Clip sampler into plastic holder and secure holder to outside of bag using safety pin.

At end of 48-hour session:

- Record stop time and date on log sheet (use time from pump display).
- Unclip sampler from holder. Immediately place into plastic bag, squeeze out any excess air and seal bag. Place plastic bag and sampler into labeled vial. Place cap on vial, making sure cap is on tightly.
- Transport samplers in orange vials back to lab. If you are not extracting filters immediately, label vial with "Exposed" and the date.
- Store exposed samplers in refrigerator.
- Extract filters in water WITHIN 15 DAYS. It is easier and more time-efficient to do this in batches than individually as they come in.

Extracting Filters:

- Label 8-ml Nalgene vial with sample numbers (2 per Ogawa sampler: 1 NOx and 1 NO2)
- Dispense 6 ml ddH2O into each vial. Use calibrated dispensette.
- Open one end of a sampler. Remove filter and put into appropriate vial into water. Screw top on tightly. Shake.
- Open other end of a sampler. Remove second filter and put into appropriate vial into water. Screw top on tightly. Shake.
- Repeat for remaining samplers.
- Shake tubes well to ensure complete extraction in water before storing.
- Store vials in refrigerator until analyzed (MUST BE ANALYZED WITHIN 90 DAYS!)

Smoke Stain Reflectometer
Standard Operating Procedures (SOP)
PHAIR Study, UBC
Version 1.0 – UBC SOP
5/26/2005

Definitions:

SSR: Smoke Stain Reflectometer
Mask: a round plate onto which the measuring head is placed during measurements
White standard: white area (circle) on the standard plate
Grey standard: grey area (circle) on the standard plate
Control filters: a clean, non-exposed filter; must be similar to those used in sampling (taken from the same lot/batch of filters as the sampling filters)
Field Blank: a control filter, not exposed to sampling air flow but otherwise handled like a regular sample filter

Equipment and Materials:

Equipment
- Smoke Stain Reflectometer: Diffusion Systems Ltd. Model 43 (M43D) or other comparable instrument
- Standard Plate (White/grey): supplied with the instrument
- Pair of tweezers

Materials
- Five (5) control filters
- PM sample filters
- PM field blank filters

<u>IMPORTANT COMMENTS PRIOR TO MEASURING REFLECTANCE: READ ON!</u>

i. Make the reflectance measurements in as dark a room as possible so as to eliminate the effects of sun and other light sources on the measurements.
ii. Do not point the measuring head toward any light source, as this may damage the instrument.
iii. To prevent contamination of the filters while performing measurements, make sure that the instruments and working environment are clean.
iv. All field blanks can be analysed according to the reflectance measurement methods described in this SOP.
v. There is some drift of readings (particularly for control filters). Rule for readings: take first number to stabilize for minimum of 5 seconds.

Procedure:

A. Preparation of the SSR for measurement (linearity check):

1. Switch on the SSR instrument and let it warm for at least 15 minutes.
2. Before attaching the measuring head, adjust the reading on the SSR to 0.0 by using the *zero* knob on the front panel of the SSR.
3. Clean the measuring head, mask, and standard plate with some alcohol, or other suitable solvent, using a lint-free cloth of Kimwipe.
4. Insert the measuring head tightly into the mask.
5. Attach the measuring head to the SSR central unit by plugging the connector into the SSR port.
6. Place the measuring head over the white standard and adjust the reflectance reading to 100.0 by using the *coarse* and *fine knobs* on the front panel.
7. Move the measuring head over the grey standard; the reading should be within the limits given for the standard plate in the manufacturer's manual (34.0 ±0.5).

B. Calibration

a. If linearity check performed in the SSR preparation steps described above yields acceptable reflectance values within the specified limits, place one of the 5 control filters (taken from the same lot/batch of filters are those used for sampling) centrally over the white standard, measure reflectance from the centre of the filter and adjust the reading to 100.0. Record this value on the data form.
b. Repeat the reflectance measurement 4 additional times, being sure to locate the measuring head in a different location than the centre each time (see Figure 1; 'Five Point Method'). Record all data on the data form.
c. Without re-adjusting the reflectance reading, measure the reflectance for the other 4 control filters using the 5-point method, and record these readings on the data form.
d. Calculate the arithmetic mean of all reflectance values for each control filter; the filter having the ***median mean*** of reflectance values is selected as the ***primary control filter*** that is used for recalibration of the SSR during the measurement of sample filters.
e. If the 5 values measured from the primary control filter have standard deviation > 0.5 units, disqualify the filter, pick a new clean filter from the batch, and redo the selection process until a suitable primary control filter is found.

Figure 1. Five Point Method of Measuring Reflectance on Filters

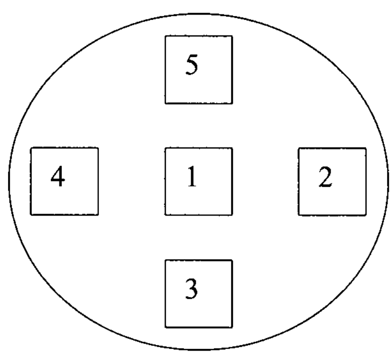


Table 1. Example Control Filter Reflectance Data Set with Averages

	Filter 1	Filter 2	Filter 3	Filter 4	Filter 5
Measurement 1	Adjust 100.0	100.1	99.7	100.1	100.4
Measurement 2	100.1	100.1	99.9	100.3	100.2
Measurement 3	100.1	100.1	100.1	100.2	100.4
Measurement 4	99.9	100.2	100.0	99.9	100.3
Measurement 5	100.1	100.0	100.0	100.4	100.1
Avg reflectance	100.03	100.10	99.94	100.18	100.28
Standard deviation	0.08	0.06	0.14	0.17	0.12
Median		100.10			

Table 1 contains example control filter weighing reflectance data for the purposes of explaining the selection process for the primary control filter. Inspection of this data, shows that the primary control filter would be FILTER 2, as it has the median standard deviation and a standard deviation < 0.5 units.

Once you have chosen the primary control filter:

- Recalibrate the SSR to 100.0 using the selected primary control filter, and measuring reflectance at its midpoint.
- Repeat calibration using the primary control filter after measuring every series of 25 filters. Record the reflectance reading of this control filter on the data form before readjusting the reading to 100.0 once again.

C. Measurement of Reflectance

I. Calibrate the SSR as described above in section 'B' of the procedure.
II. Clean the measuring head, mask, standard plate and tweezers with alcohol using a non-lint cloth or Kimwipe.
III. Ensure that the measuring head is tightly attached to the mask.
IV. Remove a sample filter from its Petri dish using tweezers and locate it centrally on the white standard.
V. Locate the measuring head with utmost caution over the sample filter and record the reflectance reading on the data form.
VI. Make 4 additional reflectance measurements per sample filter using the 5-point method and record these values on the data form.
VII. Clean the mask, standard plate, and tweezers after having measured each series of 25 sample filters (do this at the same time as the primary filter recalibration).

D. Quality Assurance

vi. At the end of each measurement session, measure reflectances again for at least 10% of the total number of filters weighed (5 times per filter, using the 5-point method). If the average reflectance of the duplicate deviates more than 3% from the original results, all of the filters measured during the measuring session will need to be re-measured (hope that this does not happen!).

Data Records and the Data Form

The following data should be recorded from the absorption coefficient measurements in the *Data Form* and computer files:

1. Date & place of measurements
2. Instrument operator ID data (name)
3. Relative humidity in the location where measurements were taken
4. Filter lot/batch # (printed on the filter package)
5. Instrument data (manufacturer name, model name/number)
6. Filter ID codes
7. Reflectance readings from all control filters and all calibrations (specify filter type in the filter code column of the data form)
8. Reflectance readings and average readings from the sample filters and field blanks

Reflectance Measurements DATA FORM

Date/Place:								Filter Batch #:		
Personnel ID:										
Instrument Data:										
Filter Code		Measurement #					Average Reflectance	Sample Vol (m^3)	Absorption Coefficient	Notes
Primary =	X	1	2	3	4	5				
Control 1										
Control 2										
Control 3										
Control 4										
Control 5										

Appendix C Monte Carlo Simulation – Impact of Mobility

Due to technical difficulties with the GPS devices, relatively few routes were available for analysis (only 35/128 samples had complete GPS route data). To investigate the impact of excluding time spent in locations other than home and work (i.e. Time spent in transit, other indoor locations), a Monte Carlo simulation approach was used to estimate the error in the exposure estimates.

The basic inputs into the calculation are shown below.

Table C.1 Variables input into the simulation

Variable (Inputs)	Variable Description	Source(s) of data
T_{Extra}	The fraction of total time in locations other than home or work	Subjects' activity log data
$Poll_{GVRD}$	Exposure concentrations for each pollutant (Poll=pollutant) using the land-use regression surfaces at all postal codes in the GVRD	All GVRD postal codes (using DMTI MEP data) and annual land-use regression surface
$Poll_{HW}$	Time-weighted estimates using land-use regression models for subjects home+work locations	LUR models and subjects' home and work geo-coded addresses

Step 1 adjusted the pollutant estimate from the subjects' home from a 48-hour period to a shorter period (1-Extra time). Step 2 calculates the additional pollutant exposure due to the non-home "extra" time period. Step 3 calculates the error in the original Home+Work estimate.

Step 1. $Poll_{H+W} \times (1 - T_{Extra}) = Poll_{H+W\_adjusted}$

Step 2. $Poll_{GVRD} \times T_{Extra} = Poll_{Extra}$

Step 3. $\dfrac{Poll_{H+W\_adjusted} + Poll_{Extra}}{Poll_{H+W}} = \%Error_{Poll}$

The calculation was simulated using a Monte Carlo technique (100,000 trials) with the Microsoft Excel add-in Crystal Ball (Decisioneering Inc. v7.2.2, Denver CO). In the simulation, values for the input variables were replaced with probability distributions. The means and standard deviations from the actual data were used to set up the distributions in Crystal Ball. The mean values used for the input variables are shown in Table C.2. Results from both Step 2 and Step 3 are also shown in Table C.3 and Table C.4.

Table C.2 Input values for simulation: Means (Standard deviation)

	Time spent in other locations (Textra)	Exposures at all GVRD postal codes using land use regression (PollGVRD)	Exposures for all subjects' home+work using Land use regression (PollH+W)
NO (ppb)	0.15 (0.07)	29.22 (15.28)	28.99 (11.0)
NO_2 (ppb)	0.15 (0.07)	17.55 (4.51)	17.16 (2.89)
Absorbance (10^{-5} m^{-1})	0.15 (0.07)	0.75 (0.35)	0.72 (14.2)
$PM_{2.5}$ (μg/m3)	0.15 (0.07)	4.11 (1.82)	4.16 (1.19)

Table C.3 Results from Step 2 - Simulation for Extra Exposure ($Poll_{Extra}$)

"Extra" Exposure from non-home, non-work locations (e.g. transit, other indoors)	Mean (5^{th}, 95^{th} Percentiles)	Standard Deviation	Median	Min - Max
NO (ppb)	4.32 (0.9 , 10.2)	3.03	3.61	0 - 30.36
NO_2 (ppb)	2.62 (0.7 , 5.1)	1.37	2.46	0 - 13.74
Absorbance (10^{-5} m^{-1})	0.11 (0.0 , 0.2)	0.07	0.10	0 - 0.77
$PM_{2.5}$ (ug/m3)	0.61 (0.1 , 1.4)	0.40	0.53	0 - 5.95

Table C.4 Results from Step 3 - Simulation for % Error

% Error from simulated "Extra" exposure	Mean (5^{th}, 95^{th} Percentiles)	Standard Deviation	Median	Min -	Max
NO (ppb)	1.41% (-11.4, 22.7)	11.6%	-0.9%	-40.4% -	213.8%
NO_2 (ppb)	0.55% (-7.3, 9.7)	5.2%	0.1%	-33.8% -	57.8%
Absorbance (10^{-5} m^{-1})	1.89% (-10.2, 21.1)	10.5%	-0.2%	-32.4% -	174.9%
$PM_{2.5}$ (ug/m3)	0.98% (-10.2, 18.0)	9.3%	-0.6%	-47.4% -	115.4%

The results from this simulation indicate that the error from ignoring mobility effects (time at locations other than home or work) is relatively small. On average, the error is from 1-2% of the total exposure. However, in some cases, the error could be much higher (up to +/- 20 %). The % error is smallest for NO_2, driven by the relatively low variability in the land-use regression surface values for that pollutant.

Appendix D PM cut-point calculation

Sampling for fine particulate was conducted with a PEM $PM_{2.5}$ sampler. This sampler is designed to be used at a 4 L/min flow rate. Because of the reasons outlined in Appendix A (detailed methods) we ran the sampler at 5 L/min. This effectively lowers the 50% cutpoint of 2.5 um to some new value. To calculate the new 50% cutpoint diameter (d_{50}) using a 5 L/min flow rate, we used the equation for the 50% collection efficiency (d_{50}) for an inertial impactor in "Aerosol Technology: Properties, Behavior, and measurement of Airborne Particles" (1) (page 118, equation 5.28):

$$d_{50}\sqrt{C_c} = \sqrt{\frac{9\eta D_{jet} Stk_{50}}{\rho_p U}} \qquad \text{Equation D.1}$$

Where U = gas velocity (m/sec) = $\dfrac{Flow}{Area_{Jet}} = \dfrac{Q}{Area}$

And:

D_{jet} = Diameter of jet

Stk_{50} = Stokes number for circular nozzle

η = constant

ρ = 1 g/cm^3

C_c = Cunningham correction factor for slip correction

We want to solve for the 50% cutpoint diameter (d_{50}) while varying only the flow rate (Q) and keeping all other factors in the equation constant. We can rearrange Equation D.1 to the following:

$$d_{50} = \sqrt{\frac{9\eta D_{jet} Stk_{50} Area_{jet}}{\rho_p C_c}} \bullet \frac{1}{\sqrt{Q}} \text{ where } \sqrt{\frac{9\eta D_{jet} Stk_{50} Area_{jet}}{\rho_p C_c}} \text{ is constant.}$$

So, $d_{50}\,\alpha\,\dfrac{1}{\sqrt{Q}}$.

In this case, d_{50} = 2.5 μm where Q = 4 L/min (if the sampler was run according to the design specification). When Q=5 L/min, we solve the following equation:

$$2.5 \times \sqrt{4} = d_{50} \times \sqrt{5}$$

Therefore, $\mathbf{d_{50} \approx 2.24}$ **μm** when the flow rate is 5 L/min.

References

(1) Hinds WC. Aerosol Technology. Properties, Behavior, and Measurement of Airborne Particles. 1st ed. USA: John Wiley & Sons, Inc.; 1982.

Appendix E Detailed Results

Overview of Specific Analyses and Results Tables

Purpose/Description	Analyses	Tables
Descriptive Results		
Describing results for all subjects in PHAIR Study	Descriptive statistics for personal characteristics, home & work characteristics, recruitment, post-birth results	Table E.1, Table E.2, Table E.4, Table E.3, Table E.5, Table E.6, Table E.7, Table E.9, Table E.8
Describing results for all samples from study population	Descriptive statistics for personal samples, ambient estimates	Table E.13, Table E.11, Table E.12, Table E.13
Describing PHAIR population	Descriptive statistics for activity data	Table E.6, Table E.7, Figure E.1
Comparisons using all measurements:		
Comparing personal measurements and ambient exposure estimates pooled from all subjects, using all methods	Pearson's correlations (Pearson's r) (log-transformed both) and Spearman's rank correlations (untransformed)	Table E.16,Table E.14, Table E.15
Predicting quartiles of personal measurements	Boxplots and K-W statistics for differences between groups and Kappa & Weighted Kappa Statistics	Figure E.2, Figure E.3, Figure E.4, Table E.17
Comparing exposure estimates for PHAIR Study population Postal Codes vs Address; LUR vs Ambient Monitors; Ambient Monitors 48-hour vs Monthly	Spearman's rank correlations (untransformed)	Table E.18, Table E.19, Table E.20, Table E.21
Comparing exposure estimates between methods for entire GVRD using all postal codes in GVRD	Various methods	Paper in progress Marshall, JM; Nethery, EN and Brauer, M
Evaluation of Mobility effects		
Understanding Mobility and it's effect on estimating exposure: GPS LUR estimates vs. LUR Home only and home+work exposure estimates and vs. Personal Measurements	Pearson Correlations for subset of routes with good GPS data	Table E.22, Table E.23
Understanding Mobility with simulations *(see further description below)*	Monte Carlo simulation for time	Table E.24
Using GPS to track personal activity patterns as compared to self reported time-activity logs	Regression (R^2) for time-activity (time spent at home and work) vs GPS predicted times	Table E.25, Figure E.5, Figure E.6

Purpose/Description	**Analyses**	**Tables**
Determinants of personal exposures		
Identifying potential predictors of personal measurements using all determinants: ambient estimates, home & work characteristics, personal characteristics, time-activity data	Univariate results: means and p-values from ANOVA for each personal measurement and determinant	Table E.26, Table E.27, Table E.28, Table E.29
Predicting Personal Exposure using all determinants *(see further description)*	Mixed effects multivariable models Variance explained and effect estimates	Table E.30, Table E.31, Table E.32, Table E.33, Table E.34, Table E.35, Table E.36
Activities of women during pregnancy		
Comparing CHAPS to PHAIR population	Differences in means; student's T-test results (p-value)	Table E.37, Table E.38, Table E.40, Table E.41, Table E.42, Table E.43
Predicting changes in activities over the course of pregnancy and season	Mixed effect models; Variances and effect estimates; Trajectory model	Table E.44, Table E.45, Table E.46, Table E.47, Table E.48, Figure E.8

Descriptive Results: Subject-specific and Sampling Data

The PHAIR Sampling study started in October 2005 and sampling was completed in August 2006. Sixty-two women participated in the study, but only 55 women completed 2 or more samples. Two women dropped out because they moved out of the study area, one miscarried, one delivered early (before her second session) and three others dropped out for unspecified reasons. Data from the first sampling session for these women was still included in the analysis.

Table E.1 Participant recruitment results

Primary Contact with Participant: "Where did you hear about the study?"	**Number of (Yes) Responses**
Word of Mouth	16
Yoga, Pilates or Athletic Class	28
Prenatal Class	2
Poster at MDS Labs	4
Midwife or Doctor	4
Poster in Community Center	3
Poster Elsewhere (Shoppers, etc)	6
Saw Study Website	2

Table E.2 Subject Questionnaire Results Descriptive Statistics (Categorical and Continuous)

Categorical Variable	Value	N	%	Value	N	%
Due Date -Season	Winter	4	6	Summer	29	47
	Spring	21	34	Fall	8	13
Sampling Date -Season	Winter		32	Summer		17
	Spring		39	Fall		13
Annual Household Income	<40k	14	11			
	40-100k	66	52			
	>100k	47	37			
Education Level Recoded	Not specified	1	2	University	24	39
	Trades or College	5	8	University>Masters	32	52
Ethnicity	White	51	82	First Nations	1	2
	Chinese	3	5	Black or African	1	2
	Indian	1	2	Other	5	8
Job Category	not working	7	11	policy/govt/planning	3	5
	healthcare	7	11	administration/office	6	10
	research	12	19	law/finance/business	4	6
	education	9	15	ministry/social work	5	8
	retail	4	6	recreation	1	2
	trades/technical	2	3	food/restaurant	1	2
	engineering	1	2			
Number of other children	0	42	68			
	1	20	32			
Rent or Own house Y/N	Rent/Other	23	38			
	Own	38	62			
Total No. Sessions	1	7	11			
	2	45	73			
	3	10	16			
Working Status	FT	39	63			
	PT	16	26			
	Not working	7	11			

Continuous Variable	Mean (Std Dev)	N	Range
Age	32 (4)	62	23-40

Table E.3 Participant Home Characteristics- Dwelling Questionnaire Results

Catagorical Variable (N=68 Homes)	**Value**	**N**	**%**
Home Air Cleaner Y/N	No	57	84
	Yes	11	16
Home Air Conditioner Y/N	No	65	96
	Yes	3	4
Home Building Type	A one-family house -detached	44	65
	Apartment building/townhouse <4 apartments	5	7
	Apartment building >5 apartments	18	26
	Boat or Other	1	1
Home Carpet Levels	0% Carpet	10	15
	up to 25% Carpet	19	28
	25-75% Carpet	19	28
	> 75% Carpet	20	29
Home Garage Y/N	No	45	66
	Yes	23	34
Home Gas Fireplace Y/N	No	53	78
	Yes	15	22
Home Gas Heating Y/N	No	40	59
	Yes	28	41
Home Gas Stove Y/N	No	40	59
	Yes	28	41
Home Heating System (primary)	Electrical	29	43
	Gas Furnace/Gas Fireplace	21	31
	Forced Air	10	15
	Hot Water/Radiator	7	10
	Unknown	1	1
Home Near or On Major Road	On Major Road (4 lanes)	11	16
	Within 50 m of Major Road	20	29
	>50 m from Major Road	37	54
Home Windows	1-4 Windows	12	18
	5-8 Windows, small	22	32
	Many (>8) windows and/or glass wall	34	50
Home Wood Fireplace	No	47	69
	Yes	21	31

Continuous Variable	Mean (Std Dev)	N	Range
Home Building Age (Years)	48.8 (31)	68	1-115
Home Ceiling Height (m)	2.6 (0)	68	2-5
Home Building Floor of Residence	1.6 (1)	68	0-10
Home Building Square Footage (m2)	118.8 (71)	68	42-437
Home No. Rooms	6.7 (3)	68	3-16
Home Volume (m3)	312.9 (206)	68	96-1197
Home No. Windows	10.6 (7)	68	2-36

Table E.4 Participant Work Characteristics-Dwelling Questionnaire Results

Variable (N=49 Workplaces)	***Value***	***N***	***%***
Work Air Cleaner Y/N	No	49	100
Work Air Conditioner	No	15	31
	Yes	34	69
Work Building Type	Detached house or duplex	5	10
	Small retail or storefront	2	4
	Small multi-story office building, or mixed use resid-retail	25	51
	Open plan retail space	2	4
	Mall complex, multiple attached stores	3	6
	High rise tower (>6 stories) or large building	11	22
	Other	1	2
Work Garage Y/N	No	30	61
	Yes	19	39
Work Heating System	Electrical	9	18
	Gas Furnace/Gas Fireplace	3	6
	Forced Air	8	16
	Hot Water/Radiator	4	8
	Unknown	25	51
Work Near or On Major Road	On Major Road (4 lanes)	24	49
	Within 50 m of Major Road	8	16
	>50 m from Major Road	17	35
Work Particle Source	No	44	90
	Yes	5	10
Work Ventilation Type	Natural Ventilation	13	27
	System Ventilation	36	73
Work Windows Classification	No Windows	5	10
	1-4 Windows	24	49
	5-8 Windows, small	8	16
	LOTS of windows, glass wall	12	24

Variable	***Mean (Std Dev)***	***N***	***Range***
Work Building Age (5 missing data) (years)	34.1 (23)	49	1-100
Work Ceiling Height (m)	3.2 (2)	49	2-15
Work Building Floor of Residence	2.4 (3)	49	0-20
Work Building Square Footage (m2)	256.1 (863)	49	4-5574
Work Volume (m3)	1291 (5111)	49	12-34000

Table E.5 Participant Activity Logs (48-hour) Results (hours/day) - Continuous Variable

Data (n=128)	Variable	Mean (Std Dev)	Range (Max-Min)
Activity Location (Log)	Indoors Home	16.1 (3.1)	9.8 -23.0
	Indoors Work	4.1 (3.1)	0.0 -9.9
	Indoors Other	1.6 (1.3)	0.0 -5.9
	Outdoors Near Home	0.1 (0.3)	0.0 -1.8
	Outdoors Away	0.3 (0.5)	0.0 -2.8
	Transit Car	0.9 (0.8)	0.0 -3.4
	Transit Bus	0.2 (0.4)	0.0 -1.9
	Walk	0.7 (0.6)	0.0 -3.1
	Bike	0.1 (0.3)	0.0 -1.7
Activity Location (Recoded)	Home (Near)	16.3 (3.2)	9.8 -23.3
	Work	4.1 (3.1)	0.0 -9.9
	Motorized Transit	1.1 (0.7)	0.0 -3.4
	Outdoors All-Bike and Walk	1.1 (0.9)	0.0 -4.2
	Transit All	1.8 (0.8)	0.0 -4.3
	Outdoors	0.4 (0.7)	0.0 -2.8
	Indoors	21.8 (1.0)	17.5 -23.5
	Non-Motorized Transit	3.0 (2.8)	0.0 -13.0
Activity Other (Log)	Cooking Y?	1.1 (1.1)	0.0 -7.1
	Smoking Nearby Y?	0.1 (0.3)	0.0 -1.7
	Windows Open Y?	7.5 (7.8)	0.0 -24.0
Physical Activity Level (Log)	Low Physical Activity	15.6 (4.5)	7.8 -24.0
	Medium Physical Activity	7.9 (4.4)	0.0 -16.2
	High Physical Activity	0.5 (0.8)	0.0 -4.8

Table E.6 Participant Activity Logs (48-hour) Results (% total time) - Continuous Variables

Data Type (n=128)	*Variable*	*Mean (Std Dev)*	*Range (Max-Min)*
Activity Location (Log)	Indoors Home	67.3% (13.0)	40.6% -95.9%
	Indoors Work	17.2% (13.1)	0.0% -41.2%
	Indoors Other	6.5% (5.5)	0.0% -24.5%
	Outdoors Near Home	0.5% (1.3)	0.0% -7.4%
	Outdoors Away	1.1% (2.3)	0.0% -11.9%
	Transit Car	3.6% (3.2)	0.0% -14.2%
	Transit Bus	0.9% (1.6)	0.0% -8.1%
	Walk	2.7% (2.6)	0.0% -13.0%
	Bike	0.2% (1.1)	0.0% -7.2%
Activity Location (Recoded)	Home (Near)	67.8% (13.3)	40.6% -96.9%
	Work	17.2% (13.1)	0.0% -41.2%
	Motorized Transit	4.5% (3.0)	0.0% -14.2%
	Outdoors All-Bike and Walk	4.6% (3.9)	0.0% -17.6%
	Transit All	7.4% (3.4)	0.0% -17.9%
	Outdoors	1.6% (2.8)	0.0% -11.9%
	Indoors	90.9% (4.4)	72.9% -97.9%
	Non-Motorized Transit	3.0% (2.8)	0.0% -13.0%
Activity Other (Log)	Cooking Y?	4.4% (4.6)	0.0% -29.7%
	Smoking Nearby Y?	0.3% (1.1)	0.0% -7.0%
	Windows Open Y?	31.1% (32.5)	0.0% -100.0%
Physical Activity Level (Log)	Low Physical Activity	64.8% (18.9)	32.6% -100.0%
	Medium Physical Activity	32.9% (18.3)	0.0% -67.4%

Data Type (n=128)	*Variable*	*Mean (Std Dev)*	*Range (Max-Min)*
	High Physical Activity	2.3% (3.4)	0.0% -20.0%

Table E.7 Participant Activity Logs Worker Results- Derived Categorical Results

Variable	*Value*	*N*	*%*
Is Worker? Y/N	No	12	9
	Yes	115	91
Worked on Sample Day-Y/N *(coded from activity log data)	No	32	25
	Yes	95	75

Figure E.1 Study subjects home and work locations

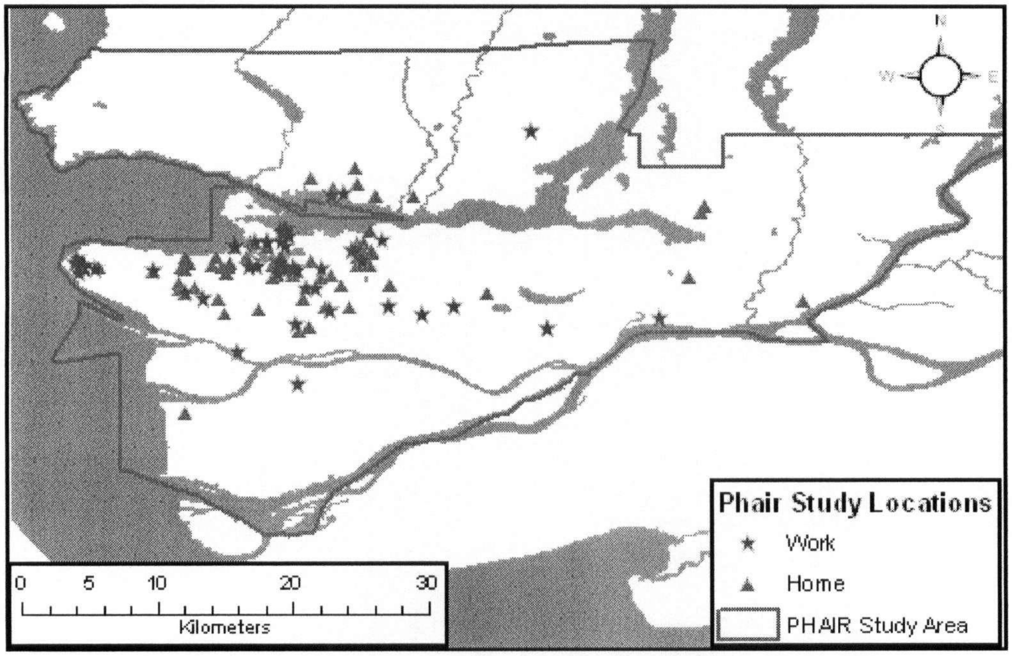


Table E.8 Post-birth questionnaire results, continuous variables and by gender

	Variable	Mean	Std Dev	Minimum	Maximum
All babies (n=55)	Gestational age at birth (weeks)	39.9	1.4	37	42
	Birth weight (grams)	3485	435	2700	4309
Girls (n=25)	Gestational age at birth (weeks)	40.0	1.6	37	42
	Birth weight (grams)	3345	309	2722	3969
Boys (n=30)	Gestational age at birth (weeks)	39.8	1.2	37	42
	Birth weight (grams)	3602	493	2700	4309

Table E.9 Post-birth questionnaire results, categorical variables

Variable (n=55 babies with post-birth data)	*Value*	*N*	*%*
Baby sex	Female	25	45
	Male	30	55
Any complications during pregnancy? [1]	No	44	80
	Yes/other	11	20
Any complications during the birth?	No	36	65
	Yes/other	19	35
C-section delivery	No	47	85
	Yes	8	15
Any health concerns with the baby?	No	47	85
	Yes/other	8	15
Baby is IUGR? [2]	No	50	91
	Yes	5	9

[1] If women noted anything other than "no" in answer to questions on the post-birth questionnaire regarding "complications during birth, pregnancy or with the baby" then response was coded as "yes".

[2] IUGR= Intrauterine Growth Retardation. This was calculated using gestational age and birth weight for the baby, and provincial birth weight charts. If the baby's birth weight was smaller than the 10th percentile, by sex, then baby was considered IUGR.

Table E.10 All exposure results for NO (personal samples, estimates)

Results for NO (ppb), n=128	Mean (Std Dev)	Geometric Mean (GSD)	Median	Range (Max-Min)	IQR
Personal Measurement	48.5 (50.3)	36.79 (2.0)	34.4	6.9-473.5	36.3
LUR Home Address Annual	28.7 (11.8)	26.57 (1.5)	27.4	6.4-94.7	10.1
LUR Home+Work Address Annual	30.0 (11.0)	28.37 (1.4)	28.2	9.0-87.4	8.97
LUR Home Address Monthly	27.2 (20.2)	21.66 (2.0)	22.2	3.8-163.3	25.6
LUR Home+Work Address Monthly	28.0 (19.0)	23.13 (1.9)	22.5	6.4-150.6	24.2
LUR Home Postal Codes Annual	28.3 (10.6)	26.27 (1.5)	26.1	5.6-84.5	9.76
LUR Home+Work Postal Codes Annual	29.9 (10.0)	28.40 (1.4)	27.8	8.3-77.7	9.95
LUR Home Postal Codes Monthly	27.0 (19.7)	21.42 (2.0)	22.3	3.6-145.6	25.5
LUR Home+Work Postal Codes Monthly	28.0 (18.4)	23.16 (1.9)	23.4	6.0-134.0	24.7
Ambient IDW, 48-hour	20.9 (24.2)	13.98 (2.3)	13.0	1.9-170.3	15.3
Ambient IDW, Monthly	17.6 (14.5)	13.86 (1.9)	11.9	4.2-82.8	13
Ambient Nearest monitor, 48-hour	23.0 (25.2)	14.01 (2.9)	16.3	0.7-121.1	19.9
Ambient Nearest monitor, Monthly	19.5 (16.5)	14.36 (2.2)	15.6	3.1-83.6	16.8

Table E.11 All exposure results for NO_2

Results for NO_2 (ppb), n=128	Mean (Std Dev)	Geometric Mean (GSD)	Median	Range (Max-Min)	IQR
Personal Measurement	18.7 (9.1)	16.95 (1.6)	17.1	4.8-75.9	10.7
LUR Home Address Annual	17.3 (3.2)	17.00 (1.2)	17.6	7.3-27.1	2.53
LUR Home+Work Address Annual	17.4 (2.9)	17.11 (1.2)	17.3	8.3-26.7	2.48
LUR Home Address Monthly	17.4 (3.7)	16.98 (1.3)	17.7	7.4-27.8	4.89
LUR Home+Work Address Monthly	17.4 (3.3)	17.09 (1.2)	17.5	8.7-26.9	4.31
LUR Home Postal Codes Annual	17.3 (3.3)	16.94 (1.2)	17.4	6.5-27.2	2.79
LUR Home+Work Postal Codes Annual	17.4 (2.9)	17.17 (1.2)	17.3	7.6-26.9	2.53
LUR Home Postal Codes Monthly	17.4 (3.8)	16.92 (1.3)	17.7	6.7-27.6	4.76
LUR Home+Work Postal Codes Monthly	17.5 (3.4)	17.16 (1.2)	17.7	7.9-26.7	4.31
Ambient IDW, 48-hour	20.2 (5.4)	19.47 (1.3)	20.3	8.8-36.3	7.07
Ambient IDW, Monthly	19.6 (4.0)	19.18 (1.2)	19.5	10.8-27.1	6.81
Ambient Nearest monitor, 48-hour	21.6 (6.6)	20.36 (1.4)	22.5	7.6-37.5	10.3
Ambient Nearest monitor, Monthly	21.0 (5.5)	20.22 (1.3)	21.6	7.6-29.0	8.72

Table E.12 All exposure results for Absorbance, PM and Levoglucosan

Results for Absorbance (10^{-5} m^{-1}), n=120	**Mean (Std Dev)**	**Geometric Mean (GSD)**	**Median**	**Range (Max-Min)**	**IQR**
Personal Measurement	0.9 (0.4)	0.82 (1.5)	0.8	0.2-2.4	0.5
LUR Home Address	0.7 (0.3)	0.68 (1.8)	0.8	0.0-1.4	0.22
LUR Home+Work Address	0.7 (0.3)	0.66 (1.8)	0.7	0.0-1.4	0.21
LUR Home Postal Codes	0.7 (0.3)	0.69 (1.7)	0.8	0.0-1.2	0.2
LUR Home+Work Postal Codes	0.7 (0.2)	0.65 (1.7)	0.7	0.1-1.3	0.23
Results for Levoglucosan (ng/m^3), n=124					
Personal Measurement	15.2 (36.6)	5.39 (3.9)	6.1	0.8-329.6	11.1
Results for $PM_{2.5}$ ($\mu g/m^3$), n=120					
Personal Measurement ($PM_{2.2}$)	11.3 (6.6)	10.02 (1.6)	9.7	4.2-45.3	5.74
LUR Home Address Annual	4.4 (1.5)	4.41 (1.3)	4.6	0.0-9.8	1.4
LUR Home+Work Address Annual	4.2 (1.2)	3.90 (1.5)	4.2	0.4-7.9	1.12
LUR Home Address Monthly	4.2 (1.5)	4.15 (1.3)	4.2	0.0-9.9	1.39
LUR Home+Work Address Monthly	4.0 (1.3)	3.67 (1.6)	4.0	0.3-7.3	1.18
LUR Home Postal Codes Annual	4.4 (1.5)	4.42 (1.3)	4.7	0.0-10.0	1.45
LUR Home+Work Postal Codes Annual	4.2 (1.2)	3.94 (1.6)	4.2	0.4-8.1	1.35
LUR Home Postal Codes Monthly	4.2 (1.5)	4.17 (1.4)	4.2	0.0-10.1	1.48
LUR Home+Work Postal Codes Monthly	4.0 (1.3)	3.71 (1.6)	4.0	0.3-7.5	1.29
Ambient IDW, 48-hour	5.3 (2.8)	4.65 (1.7)	4.6	1.5-15.0	3.1
Ambient IDW, Monthly	4.8 (1.3)	4.63 (1.3)	4.7	2.6-9.9	1.75
Ambient Nearest monitor, 48-hour	5.3 (2.9)	4.67 (1.7)	4.8	1.2-15.1	3.09
Ambient Nearest monitor, Monthly	4.8 (1.4)	4.61 (1.3)	4.9	2.0-9.8	1.61

Table E.13 Personal Sampling Results Limit of Detection and Precision

Measured Sample	**LOD**	**% below LOD**	**Precision (CV)**
NO (ppb)	8.8	1%	5% *
NO2 (ppb)	4.5	0	5% *
Absorbance (10^{-5} m^{-1})	0.1	0	6% **
PM2.1 ($\mu g/m^3$)	1	0	8.4% **
Levoglucosan (ng/m^3)	0.8	14%	

Comparing Personal Measurements to Models

Table E.14 Spearman Rho Correlations between Personal Measured Results and Model Estimates (untransformed)

Personal Measured Compared to Model:	**Spearman Rho Correlations**			
	NO (n=126)	**NO_2 (n=126)**	**Absorbance (n=119)**	**$PM_{2.1}$ (n=123)**
Ambient Monitoring IDW Monthly	0.56	0.07	0.27	0.13
Ambient Monitoring Nearest Monthly[1]	0.54	0.16	0.21	0.07
Land Use Regression Home Postal Code[2]	0.49	0.18 **	-0.11 **	0.07

Table E.15 Correlations for personal measures and models (Pearson's r, log-transformed), NO and NO_2

Exposure Estimate compared to personal measurements Pearson's r correlations	**NO Log Personal Measured (n=128)**	**NO2 Log Personal Measured (n=128)**
LUR Home Address Annual	0.05	**0.20**
LUR Home+Work Address Annual	0.11	**0.30**
LUR Home Address Monthly	**0.49**	0.12
LUR Home+Work Address Monthly	**0.55**	0.20
LUR Home Postal Code Annual	0.07	**0.18**
LUR Home+Work Postal Code Annual	0.10	**0.28**
LUR Home Postal Code Monthly	**0.49**	0.11
LUR Home+Work Postal Code Monthly	**0.55**	0.18
Ambient IDW, 48-hour	**0.59**	0.15
Ambient IDW, Monthly	**0.56**	0.07
Ambient Nearest monitor, 48-hour	**0.55**	0.22
Ambient Nearest monitor, Monthly	**0.54**	0.16

Table E.16 All correlations for personal samples (Pearson's r, log-transformed), Absorbance and PM

Exposure Estimate compared to personal measurements Pearson's r correlations	**Absorbance Log Personal Measured (n=120)**	**$PM_{2.2}$ Log Personal Measured (n=124)**
LUR Home Address Annual	-0.13	-0.01
LUR Home+Work Address Annual	-0.11	0.01
LUR Home Address Monthly	n/a	0.08
LUR Home+Work Address Monthly	n/a	0.12
LUR Home Postal Code Annual	-0.11	-0.02
LUR Home+Work Postal Code Annual	-0.10	-0.00
LUR Home Postal Code Monthly	n/a	0.07
LUR Home+Work Postal Code Monthly	n/a	0.10
Ambient IDW, 48-hour	**0.50**	**0.29**
Ambient IDW, Monthly	**0.27**	0.13
Ambient Nearest monitor, 48-hour	**0.48**	**0.29**
Ambient Nearest monitor, Monthly	**0.21**	0.07

1 Measured Absorbance and $PM_{2.1}$ are both compared to Ambient Modeled $PM_{2.5}$

2 With seasonal adjustment, except Absorbance (no adjustment)

Figure E.2 Boxplots of personal measurements by quartiles of land-use regression estimates for all pollutants: Left to right (NO, NO_2, Absorbance, PM)

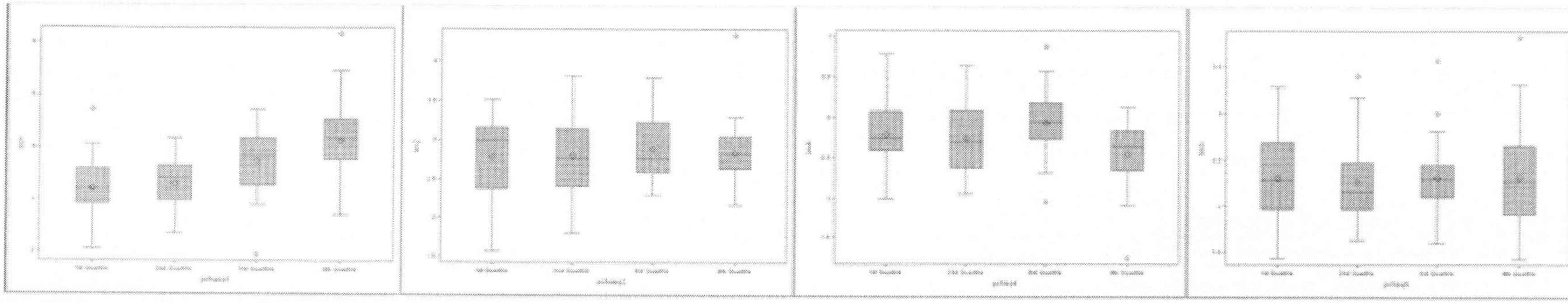


Figure E.3 Boxplots of personal measurements by quartiles of ambient monitor estimates (48-hour) *nearest monitor* for all pollutants

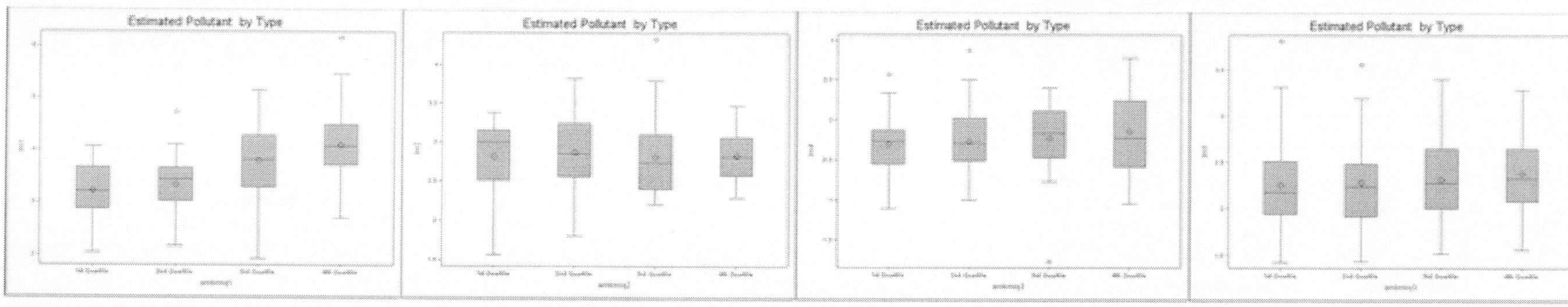


Figure E.4 Boxplots of personal measurements by quartiles of ambient monitor estimates (48-hour) *inverse-distance weighted* method for all pollutants

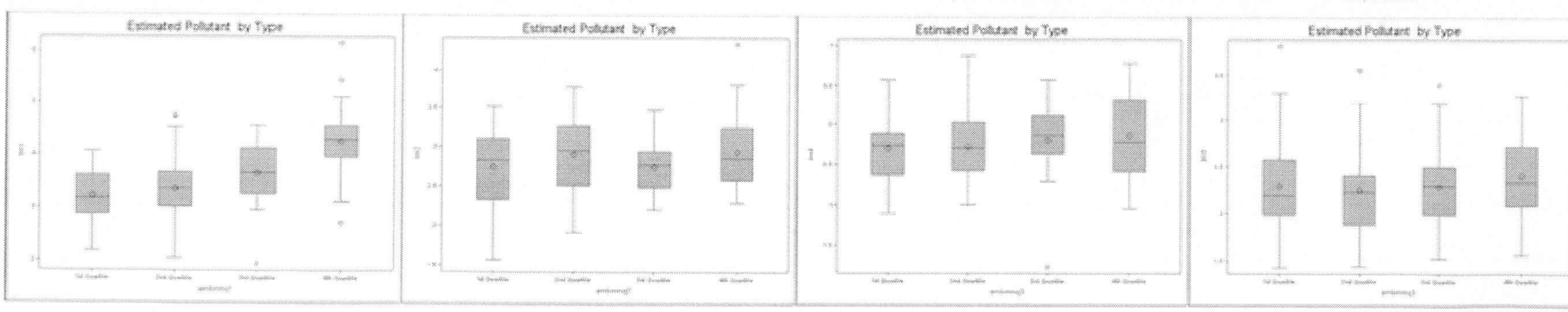


Table E.17 Kruskal-wallis p-values for distributions of personal measurements within quartiles of exposure estimates by method

	Kruskal-wallis non-parametric statistics comparing to personal measurements (p-values)			
Exposure Estimates (Quartiles)	**NO**	**NO2**	**ABS compared to PM10**	**PM2.1 compared to PM25**
LUR Address Home	<.0001	0.934	0.861	0.817
LUR Address Home+Work	<.0001	0.702	0.638	0.580
LUR Address Home Annual	0.023	0.038	0.019	0.837
LUR Postal code Home	<.0001	0.934	0.861	0.817
LUR Postal code Home+Work	<.0001	0.702	0.638	0.580
Ambient 48-hour IDW Quartile	<.0001	0.917	0.001	0.016
Ambient 48-hour Nearest	<.0001	0.144	0.001	0.037
Ambient Month IDW Quartile	<.0001	0.798	0.335	0.652
Ambient Month Nearest	<.0001	0.251	0.020	0.544

Table E.18 Spearman Rho correlations for Land Use Regression vs. Interpolation Models

Land Use Regression Compared to Interpolation Models:	Spearman Rho Correlations			
(n=126)	**NO**	**NO_2**	**Absorbance**	**$PM_{2.1}$**
LUR and Ambient IDW (Monthly)	0.78	0.66	-0.09	0.15
LUR and Ambient Nearest Monitor (Monthly)	0.69	0.55	-0.13	0.10
LUR and Ambient IDW (Time-specific)	0.66	0.50	-0.06	0.10
LUR and Ambient Nearest Monitor (Time-specific)	0.56	0.45	-0.10	0.08

Table E.19 Spearman Rho correlations for LUR using Postal Code or Address Geocoding compared to Personal Samples

Personal Measured Compared to Model:	Spearman Rho Correlations			
(n=126)	**NO**	**NO_2**	**Absorbance**	**$PM_{2.1}$**
Land Use Regression† Home Address	0.43	-0.03	-0.13	0.08
Land Use Regression† Home Postal Code	0.44	-0.03	-0.09	0.07

Table E.20 Spearman Rho correlations for comparing LUR Postal Code vs Address Geocoding

Land Use Regression† Estimates Using Postal Codes vs Addresses (n=126)	Spearman Rho Correlations NO	NO_2	Absorbance	$PM_{2.1}$
Home Postal Codes vs. Addresses	0.99	0.99	0.96	0.99
Work Postal Codes vs. Addresses	0.95	0.95	0.87	0.97
	Weighted Kappa (by Quartiles)			
Home Postal Codes vs. Addresses	0.96	0.94	0.87	0.90
Work Postal Codes vs. Addresses	0.85	0.89	0.66	0.89

Table E.21 Spearman correlations comparing ambient monitoring methods for monthly vs time-specific (48-hour) estimates

Interpolation Models Using Monthly vs Time-Specific Methods (n=126)	Spearman Rho Correlations NO	NO_2	$PM_{2.5}$	PM_{10}
Inverse Distance Weight – Month vs Time-Specific	0.85	0.76	0.54	0.60
Nearest Monitor – Month vs Time-Specific	0.87	0.78	0.52	0.58

Incorporating Mobility

Table E.22 Spearman correlations using GPS Subset: comparing land-use regression estimates using home only, home+work, GPS route and personal measurements

Personal Measured Compared to Land Use Regression* Model Estimate	Spearman Rho Correlations			
(GPS Subset)	NO (n=35)	NO_2 (n=35)	Absorbance (n=34)	$PM_{2.1}$ (n=34)
Home Only	0.63	0.27	-0.18	0.36
Combined Home+Work	0.72	0.34	-0.18	0.30
GPS Route	0.75	0.37	-0.16	0.27

Table E.23 Spearman correlations using GPS subset: comparing between methods: home, home+work vs GPS route

Land Use Regression* Model Estimate Home, Home+Work Compared to GPS Route	Spearman Rho Correlations			
(GPS Subset)	NO (n=35)	NO_2 (n=35)	Absorbance (n=34)	$PM_{2.1}$ (n=34)
Home Only – GPS Route	0.92	0.83	0.84	0.87
Combined Home+Work – GPS Route	0.98	0.97	0.95	0.94

Table E.24 Time in Transit Simulation - % Error predicted from excluding time in traffic

% Error from Excluding Time in Transit (Monte Carlo simulation results)	Mean (5th, 95th Percentiles)	Standard Deviation	Median	Min -	Max
NO	1.41% (-11.4, 22.7)	11.6%	-0.9%	-40.4% -	213.8%
NO_2	0.55% (-7.3, 9.7)	5.2%	0.1%	-33.8% -	57.8%
Absorbance	1.89% (-10.2, 21.1)	10.5%	-0.2%	-32.4% -	174.9%
$PM_{2.5}$	0.98% (-10.2, 18.0)	9.3%	-0.6%	-47.4% -	115.4%

Figure E.5 GPS Time at home vs. activity log (regression plot)

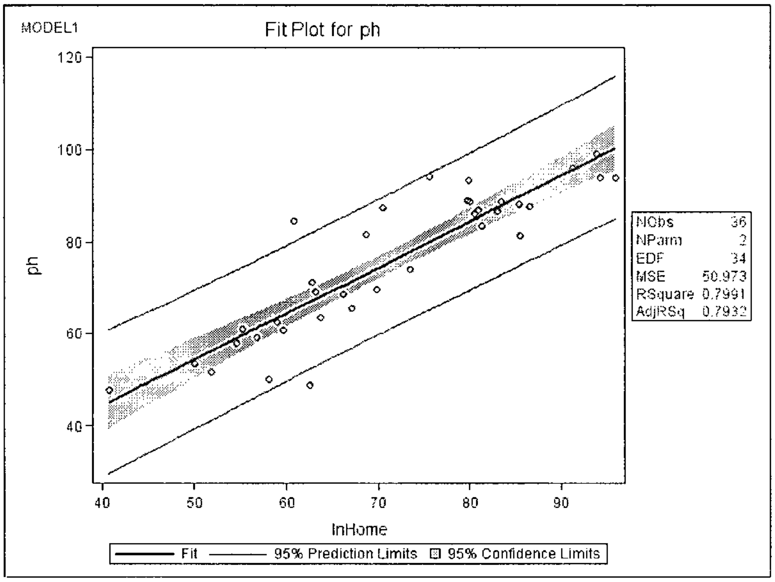


Figure E.6 GPS time at work vs. activity log (regression plot)

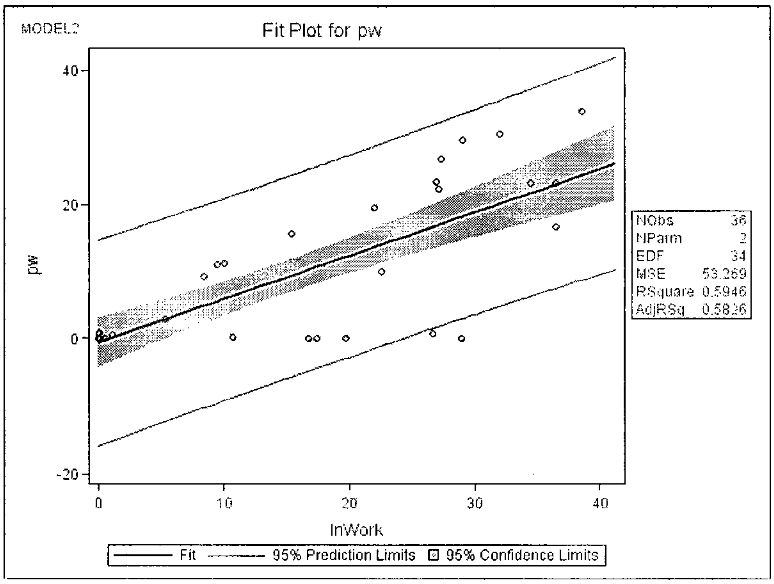


Table E.25 Comparison of GPS based activity data to self reported time-activity logs

	Home		Work	
Statistic	**GPS**	**Activity Log**	**GPS**	**Activity Log**
Mean (standard deviation)	76.0 (15.5)	67.5 (13.3)	8.5 (11.2)	17.3 (13.1)
N	37	127	37	127
Pearson's r (GPS vs. Activity Log)	0.914		0.771	

Table E.26 Anova (p-values and F statistic) results for personal measurements (dependent) and ambient exposure estimates in univariate analysis

	Log NO		Log NO_2		Log Abs		Log $PM_{2.2}$	
Independent Variable Description	**Model Anova P-value**	**F-value**	**Model Anova P-value**	**F-value**	**Model Anova P-value**	**F-value**	**Model Anova P-value**	**F-value**
LUR Home Address Annual	0.5184	0.42	0.0221	5.37	0.1123	2.56	0.8817	0.02
LUR Home Address Monthly	<.0001	40.23	0.1634	1.97	n/a		0.2265	1.48
LUR Home+Work Address Monthly	<.0001	54.97	0.027	5.01	n/a		0.1326	2.29
LUR Home Postal Monthly	<.0001	40.23	0.1634	1.97	n/a		0.2265	1.48
LUR Home+Work Postal Monthly	<.0001	54.97	0.027	5.01	n/a		0.1326	2.29
Ambient 48-hour IDW -NO or NO2(ppb)	<.0001	53.63	0.1421	2.18				
Ambient 48-hour Near -NO or NO2(ppb)	<.0001	62.18	0.0168	5.88				
Ambient Month IDW -NO or NO2(ppb)	<.0001	46.21	0.7956	0.07				
Ambient Month Near -NO or NO2(ppb)	<.0001	52.27	0.1359	2.25				
Ambient 48-hour IDW -PM25(ug/m3)					<.0001	47.09	0.0006	12.45
Ambient 48-hour Near -PM25(ug/m3)					<.0001	38.61	0.0008	11.83
Ambient Month IDW -PM25(ug/m3)					0.0021	9.93	0.1361	2.25
Ambient Month Near -PM25(ug/m3)					0.0132	6.33	0.3366	0.93

Table E.27 Anova and Kruskal-wallis p-values for categorical determinants and personal measurements (dependent)

Categoricals	NO		NO_2		Absorbance		$PM_{2.2}$	
Determinant (independent)	**ANOVA**	**KW**	**ANOVA**	**KW**	**ANOVA**	**KW**	**ANOVA**	**KW**
Home Air Cleaner Y/N	0.326	0.236	0.610	0.771	0.105	0.097	0.196	0.202
Home Air Conditioner Y/N	0.400	0.116	0.227	0.230	0.096	0.061	0.196	0.082
Home Building Age Classified	0.084	0.008	0.095	0.227	0.778	0.865	0.146	0.492
Home Building Type-Recoded	0.890	0.187	0.787	0.929	0.933	0.947	0.872	0.665
Home Carpet Levels	0.142	0.022	0.011	0.056	0.658	0.387	0.904	0.514
Home Garage Y/N	0.044	0.027	0.379	0.716	0.356	0.776	0.254	0.323
Home Gas Fireplace Y/N	0.803	0.080	0.099	0.109	0.317	0.491	0.119	0.188
Home Gas Stove Y/N	< .0001	< .0001	0.000	0.001	0.055	0.020	0.030	0.065
Home Gas Heating Y/N	0.485	0.004	0.925	0.930	0.232	0.107	0.941	0.892
Home Near or On Major Road	0.925	0.056	0.019	0.011	0.129	0.174	0.305	0.361
Home Windows Classification V2	0.077	0.024	0.050	0.169	0.781	0.693	0.190	0.258
Home Wood Fireplace Y/N	0.080	0.148	0.116	0.201	0.862	0.829	0.214	0.109
Sample Season- 2 Lev: Winter=1/Summer=0	< .0001	< .0001	0.533	0.080	0.032	0.050	0.945	0.570
Sample Season- 4 Levels	< .0001	< .0001	0.056	0.001	0.006	0.003	0.205	0.471
Subject Education Level Recoded	0.104	0.280	0.030	0.334	0.188	0.451	0.001	0.151
Subject Ethnicity	0.941	0.578	0.724	0.324	0.745	0.888	0.875	0.867
Subject Annual Household Income	0.012	0.121	0.000	0.003	0.893	0.942	0.000	0.022
Subject Number of other children	0.430	0.799	0.357	0.659	0.342	0.137	0.385	0.288
Subject Rent or Own house Y/N	0.863	0.227	0.377	0.514	0.239	0.314	0.187	0.322
Subject Total No. Sessions	0.684	0.863	0.322	0.483	0.849	0.864	0.361	0.374
Subject Trimester of Pregnancy on Sample Day	0.104	0.003	0.742	0.605	0.257	0.083	0.308	0.721
Subject Weeks of Pregnancy on Sample Day	0.555	0.145	0.085	0.035	0.552	0.373	0.154	0.200
Subject Job Category-recoded	0.343	0.036	0.018	0.014	0.517	0.317	0.800	0.377
Subject Working Status	0.402	0.216	0.197	0.156	0.876	0.790	0.354	0.270
Work Air Conditioner Y/N	0.044	0.013	0.008	0.003	0.274	0.600	0.446	0.949
Work Building Age Classified	0.889	0.321	0.070	0.011	0.768	0.621	0.251	0.106
Work Building Type	0.708	0.150	0.263	0.037	0.939	0.730	0.946	0.404
Work Garage Y/N	0.022	0.121	0.002	0.006	0.614	0.866	0.804	0.667
Work Near or On Major Road	0.224	0.014	0.634	0.312	0.856	0.610	0.753	0.826
Work Particle Sources at Work? Y/N	0.446	0.253	0.014	0.002	0.427	0.667	0.705	0.749
Work Ventilation Type	0.085	0.028	0.075	0.041	0.461	0.951	1.000	0.323
Work Windows Classification	0.692	0.569	0.071	0.027	0.768	0.663	0.162	0.094

Table E.28 ANOVA (p-value) for continuous determinants and personal measurements (dependent)

	Regression Anova p-value for personal measured (dependent)			
Independent Variable	**NO**	**NO_2**	**ABS**	**$PM_{2.2}$**
Activity Log -Physical activity =High	0.395	0.285	0.602	0.533
Activity Log -Cooking (yes)	0.705	0.913	0.197	0.059
Activity Log -Smoking (yes)	0.197	0.420	0.850	0.161
Activity Log -Windows Open (yes)	0.000	0.000	0.120	0.590
Activity Log -Sampler On (yes)	0.131	0.572	0.786	0.329
Activity Log -Outdoors All-Bike and Walk	0.007	0.030	0.539	0.028
Activity Log -All Motorized Transit	0.404	0.556	0.220	0.393
Activity Log -Near Home-Indoors and Out	0.596	0.053	0.072	0.505
Distance Home to Nearest Hwy (m)	0.025	0.030	0.071	0.243
Distance Work to Nearest Hwy (m)	0.791	0.138	0.892	0.644
Distance Home to Major Road (m)	0.497	0.047	0.720	0.295
Distance Work to Major Road (m)	0.544	0.636	0.872	0.916
Home Building Floor of Residence	0.640	0.143	0.560	0.171
Home Building Square Footage (m2)	0.370	0.001	0.044	0.017
Home No. Rooms	0.295	0.002	0.077	0.002
Home Volume (m3)	0.329	0.002	0.042	0.027
Home No. Windows	0.248	0.003	0.698	0.087
Subject Age	0.139	0.876	0.022	0.883
Subject Number of other children	0.691	0.689	0.127	0.245
Subject Total No. Sessions	0.559	0.229	0.823	0.309
Work Building Age-Dwelling Q	0.032	0.027	0.218	0.214
Work Building Floor of Residence	0.561	0.793	0.234	0.159
Work Building Square Footage (m2)	0.034	0.213	0.101	0.318
Work Volume-Log_e (m3)	0.171	0.389	0.047	0.067

Table E.29 List of determinants (excluding exposure estimates) initially considered for mixed-effect models by pollutant

Type	Determinant	NO Initial	NO_2 Initial	ABS Initial	$PM_{2.2}$ Initial	Cat or Cont
Activity	Cooking (% time)	x			x	cont
Activity	Windows Open (% time)	x	x	x		cont
Activity	Outdoors All-Bike and Walk (% time)	x	x		x	cont
Activity	Near/At Home (% time)		x	x		cont
Activity	Cooking with Gas stove (% time)					cont
Home	Air Cleaner Y/N			x		cat
Home	Air Conditioner Y/N			x	x	cat
Home	Building Floor of Residence				x	cat
Home	Carpet Levels (No carpet, 0-25%,25-75%, All carpeted)	x	x			cat
Home	Garage Y/N	x				cat
Home	Gas Fireplace Y/N	x	x			cat
Home	Gas Heating Y/N	x		x		cat
Home	Gas Stove Y/N	x	x	x	x	cat
Home	Near or On Major Road (On major road, within 50m, >50 m)	x	x	x		cat
Home	No. Rooms		x	x	x	cont
Home	Windows Classification (1-4 windows, 5-8 windows, >8 windows)	x				cat
Home	Wood Fireplace Y/N	x				cat
Subject	Subject Age (years)			x		cont
Subject	Subject Annual Household Income (7 levels)	x	x		x	cat
Subject	Subject Job Category (13 levels)		x			cat
Work	Air Conditioner Y/N	x				cat
Work	Building Age (years, estimated)	x	x			cont
Work	Building Square Footage (m^2)	x				cont
Work	Building Type		x			cat
Work	Garage Y/N	x	x			cat
Work	Particle Sources at work Y/N		x			cat
Work	Ventilation Type (natural or system)	x	x			cat
Work	Volume-Log_e (m3)			x	x	cont
Work	Windows Classification (3 levels)		x			cat

Table E.30 Variance explained in NO mixed effect models (Ambient IDW)

NO Models *(Model with subject only is baseline)*	**Variance Component (95% Confidence Limits)**		**% Variance Explained (compared to baseline)**		
Model Definition (fixed and random effects)	**Within Subject (σ_{ws})**	**Between Subject (σ_{BS})**	σ_{ws}	σ_{BS}	**Total**
Subject +	0.33 (0.24 ,0.48)	0.19 (0.10 ,0.46)	.	.	.
Subject + Home Gas Stove	0.31 (0.22 ,0.45)	0.08 (0.03 ,0.48)	6	58	25
Subject + Time Outdoors	0.30 (0.22 ,0.44)	0.19 (0.10 ,0.46)	8	-1	5
Subject + LUR Home Postal (month)	0.21 (0.15 ,0.31)	0.18 (0.11 ,0.37)	36	3	24
Subject + LUR NO Home Postal (month)	0.21 (0.15 ,0.30)	0.15 (0.09 ,0.33)	37	19	30
Subject + Monitor-based NO (month)	0.21 (0.15 ,0.30)	0.16 (0.10 ,0.34)	38	13	29
Subject + LUR NO Home Address (month)	0.20 (0.15 ,0.30)	0.19 (0.11 ,0.37)	38	-1	24
Subject + LUR NO Home and Work Address (month)	0.21 (0.15 ,0.30)	0.15 (0.09 ,0.33)	37	19	30
Subject + Monitor-based NO (48-hour)	0.18 (0.13 ,0.26)	0.16 (0.10 ,0.32)	46	14	34
Subject + Monitor-based NO (month) + LUR NO Home Postal (month)	0.18 (0.13 ,0.25)	0.15 (0.09 ,0.31)	47	19	37
Subject + Monitor-based NO (48-hour) + LUR NO Home and Work Address (month)	0.15 (0.11 ,0.22)	0.15 (0.09 ,0.29)	54	20	41
Subject + Time Outdoors + Home Gas Stove	0.28 (0.20 ,0.41)	0.08 (0.03 ,0.41)	15	57	30
Subject + Time Outdoors + LUR Home Postal (month) + Home Gas Stove	0.21 (0.15 ,0.31)	0.05 (0.02 ,0.39)	36	76	50
Subject + Time Outdoors + LUR NO Home Postal (month) + Home Gas Stove	0.21 (0.15 ,0.30)	0.04 (0.01 ,0.51)	37	80	53
Subject + Time Outdoors + Monitor-based NO (month) + Home Gas Stove	0.19 (0.14 ,0.27)	0.07 (0.04 ,0.24)	44	60	50
Subject + Time Outdoors + LUR NO Home Address (month) + Home Gas Stove	0.21 (0.15 ,0.30)	0.06 (0.02 ,0.30)	37	70	49
Subject + Time Outdoors + LUR NO Home and Work Address (month) + Home Gas Stove	0.21 (0.15 ,0.30)	0.04 (0.01 ,0.59)	37	80	52
Subject + Time Outdoors + Monitor-based NO (48-hour) + Home Gas Stove	0.17 (0.12 ,0.24)	0.06 (0.03 ,0.22)	50	67	56
Subject + Time Outdoors + LUR NO Home Postal (month) + Monitor-based NO (month) + Home Gas Stove	0.17 (0.13 ,0.25)	0.05 (0.02 ,0.25)	48	74	57
Subject + Time Outdoors + LUR NO Home and Work Address (month) + Monitor-based NO (48-hour) + Home Gas Stove	0.15 (0.11 ,0.22)	0.05 (0.02 ,0.22)	53	76	61

Table E.31 Variance explained in NO_2 mixed effect models

NO_2 Models *(Model with subject only is baseline)*	**Variance Component (95% Confidence Limits)**		**% Variance Explained (compared to baseline)**		
Model Definition (fixed and random effects)	**Within Subject (σ_{WS})**	**Between Subject (σ_{BS})**	σ_{WS}	σ_{BS}	**Total**
Subject +	0.09 (0.06 ,0.12)	0.11 (0.07 ,0.20)	.	.	.
Subject + Home Gas Stove	0.08 (0.06 ,0.12)	0.10 (0.06 ,0.18)	4	10	7
Subject + No. Rooms	0.09 (0.06 ,0.13)	0.10 (0.06 ,0.18)	-2	12	6
Subject + Time At/Near Home	0.08 (0.06 ,0.12)	0.11 (0.07 ,0.20)	3	2	2
Subject + No. Rooms + Time At/Near Home + Home Gas Stove	0.08 (0.06 ,0.12)	0.08 (0.05 ,0.15)	5	32	21
Subject + LUR NO_2 Home Postal (year)	0.08 (0.06 ,0.12)	0.11 (0.07 ,0.20)	1	2	2
Subject + LUR NO_2 Home and Work Postal (year)	0.08 (0.06 ,0.12)	0.10 (0.07 ,0.19)	3	7	6
Subject + LUR NO_2 Home Address (year)	0.08 (0.06 ,0.12)	0.11 (0.07 ,0.20)	1	4	3
Subject + LUR NO_2 Home and Work Address (year)	0.08 (0.06 ,0.12)	0.10 (0.06 ,0.19)	4	9	7
Subject + No. Rooms + Time At/Near Home + LUR NO_2 Home Postal (year) + Home Gas Stove	0.08 (0.06 ,0.12)	0.07 (0.04 ,0.15)	7	36	23
Subject + No. Rooms + Time At/Near Home + LUR NO_2 Home and Work Postal (year) + Home Gas Stove	0.08 (0.06 ,0.12)	0.06 (0.04 ,0.14)	7	42	27
Subject + No. Rooms + Time At/Near Home + LUR NO_2 Home Address (year) + Home Gas Stove	0.08 (0.06 ,0.12)	0.07 (0.04 ,0.14)	6	37	24
Subject + No. Rooms + Time At/Near Home + LUR NO_2 Home and Work Address (year) + Home Gas Stove	0.08 (0.06 ,0.11)	0.06 (0.04 ,0.13)	8	43	28

Table E.32 Variance explained in Absorbance mixed effect models (Ambient IDW)

Absorbance Models *(Model with subject only is baseline)*	**Variance Component (95% Confidence Limits)**		**% Variance Explained (compared to baseline)**		
Model Definition (fixed and random effects)	**Within Subject (σ_{ws})**	**Between Subject (σ_{BS})**	σ_{ws}	σ_{BS}	**Total**
Subject +	0.17 (0.12 ,0.25)	0.02 (0.01 ,1.34)	.	.	.
Subject + Home Gas Stove	0.16 (0.12 ,0.25)	0.02 (0.00 ,14.63)	0	27	4
Subject + Home Air Conditioning	0.17 (0.12 ,0.25)	0.02 (0.00 ,3.84)	0	15	2
Subject + No. Rooms	0.16 (0.11 ,0.24)	0.03 (0.01 ,0.67)	4	-12	2
Subject + Wood Smoke (log levo)	0.10 (0.08 ,0.16)	0.03 (0.01 ,0.16)	36	-24	29
Subject + Monitor-based IDW $PM_{2.5}$ (month)	0.15 (0.10 ,0.22)	0.03 (0.01 ,0.42)	11	-19	8
Subject + Monitor-based IDW $PM_{2.5}$ (48-hour)	0.09 (0.07 ,0.14)	0.05 (0.02 ,0.13)	44	-91	27
Subject + No. Rooms + Wood Smoke (log levo) + Home Gas Stove + Home Air Conditioning	0.11 (0.08 ,0.16)	0.02 (0.01 ,0.32)	36	14	33
Subject + No. Rooms + Wood Smoke (log levo) Monitor-based IDW $PM_{2.5}$ (month) + Home Gas Stove + Home Air Conditioning	0.09 (0.07 ,0.14)	0.02 (0.01 ,0.19)	43	5	38
Subject + No. Rooms + Wood Smoke (log levo) + Monitor-based IDW $PM_{2.5}$ (48-hour) + Home Gas Stove + Home Air Conditioning	0.05 (0.04 ,0.08)	0.03 (0.01 ,0.08)	68	-15	57

Table E.33 Variance explained in $PM_{2.2}$ mixed effect models

$PM_{2.2}$ Models *(Model with subject only is baseline)*	**Variance Component (95% Confidence Limits)**		**% Variance Explained (compared to baseline)**		
Model Definition (fixed and random effects)	**Within Subject (σ_{ws})**	**Between Subject (σ_{BS})**	σ_{ws}	σ_{BS}	**Total**
Subject +	0.17 (0.12 ,0.25)	0.06 (0.03 ,0.25)	.	.	.
Subject + Home Gas Stove	0.17 (0.12 ,0.24)	0.05 (0.02 ,0.24)	2	9	4
Subject + Home Air Conditioning	0.17 (0.12 ,0.25)	0.06 (0.03 ,0.26)	0	3	1
Subject + No. Rooms	0.17 (0.12 ,0.25)	0.04 (0.02 ,0.30)	0	26	7
Subject + Time Cooking*Gas Stove	0.17 (0.12 ,0.25)	0.06 (0.03 ,0.25)	1	-5	-1
Subject + Monitor-based $PM_{2.5}$ (month)	0.15 (0.11 ,0.23)	0.07 (0.04 ,0.23)	9	-25	0
Subject + Monitor-based $PM_{2.5}$ (48-hour)	0.14 (0.10 ,0.21)	0.07 (0.03 ,0.20)	18	-16	9
Subject + No. Rooms + Time Cooking*Gas Stove + Home Gas Stove + Home Air Conditioning	0.16 (0.12 ,0.24)	0.03 (0.01 ,0.64)	4	52	17
Subject + No. Rooms + Time Cooking*Gas Stove Monitor-based $PM_{2.5}$ (month) + Home Gas Stove + Home Air Conditioning	0.15 (0.10 ,0.22)	0.04 (0.02 ,0.26)	14	29	18
Subject + No. Rooms + Time Cooking*Gas Stove + Monitor-based $PM_{2.5}$ (48-hour) + Home Gas Stove + Home Air Conditioning	0.13 (0.09 ,0.19)	0.03 (0.01 ,0.24)	24	43	29

Table E.34 Percentage change (95 % confidence interval) in personal measurements for change in fixed effect, excluding ambient estimates, from final (Adjusted) regression models.

Variable Influencing Exposure	**Increase in variable**[1]	**Resulting percent change (95% confidence interval) in personal measured pollutant**[2]			
		NO (%)	**NO_2 (%)**	**ABS (%)**	**$PM_{2.2}$ (%)**
Home Gas Stove Presence	Yes	89 (58, 127)	44 (21, 70)	20 (5, 37)	35 (6, 70)
Home Number of Rooms	1 room	--	-4 (-6, -1)	-3 (-5, -1)	-5 (-8, -2)
Home Air Conditioning	Yes	--	--	-41 (-59, -17)	-42 (-64, -7)
Outdoors	1 hr/day	-8 (-15, 1)	--	--	--
At/Near Home	1 hr/day	--	-3 (-5, -1)	--	--
Cooking and Gas Stove in home	1 hr/day	--	--	--	8 (0, 16)
Wood smoke tracer[3]	log 1 ng/m^3	--	--	38 (26, 50)	--
LUR Home and Work (Address)	IQR	28 (14, 44)	11 (4, 19)	--	--
Monitor-based IDW 48-hour	IQR	19 (12, 26)	--	28 (21, 35)	21 (12, 31)
Intercept		18 (15, 22) ppb	15 (8, 28) ppb	0.7 (0.6, 0.8) (m^{-1} 10^{-5})	8.5 (6.5, 11.1) μg/m^3

[1] Reported change in exposure determinant chosen for ease of interpretation (ie. 1 h/day or 1 room) for all home and activity variables, or using interquartile ranges for outdoor pollution levels.
[2] -- Variable not significant in the final model for that pollutant.
[3] 'Wood smoke' refers to the levoglucosan concentration measured in personal samples.

Table E.35 Percentage change in personal exposure for IQR increase - comparing 'Adjusted' and 'Unadjusted' models (using methods from Chapter 3): Each line represents a complete model

IQR are: NO (Traffic) = 24.5 ppb; NO (Monitor) = 15 ppb; NO_2 (Traffic)=2.5 ppb; $PM_{2.5}$ = 3.1 $\mu g/m^3$.

		Percentage change in personal measurements for IQR change in:	
Personal Pollutant (dependent)		**Traffic-based (LUR Home+Work) (address)**	**Monitor-based (IDW) (48-hour)**
NO	Unadjusted	63 (44, 84)	--
(only LUR)	Adjusted	54 (38, 73)	--
NO	Unadjusted	--	30 (23, 38)
(only Ambient)	Adjusted	--	27 (20, 33)
NO Combined	Unadjusted	32 (16, 51)	21 (13, 29)
(LUR+Ambient)	Adjusted	28 (14, 44)	19 (12, 26)
NO_2[1]	Unadjusted	12 (4, 20)	--
	Adjusted	11 (4, 19)	--
Absorbance	Unadjusted	--	31 (22, 40)
	Adjusted	--	28 (21, 35)
$PM_{2.1}$	Unadjusted	--	20 (10, 30)
	Adjusted	--	21 (12, 31)

[1] NO_2 models all use *annual* LUR model rather than monthly model, NO models use monthly adjusted model

Table E.36 Percentage change in personal exposure for IQR increase –comparing 'Adjusted' and 'Unadjusted' models (using methods from Chapter 2) –NOTE Each model has only one outdoor pollution effect estimate (rows do not represent combined models)

IQR are: NO: LUR Home = 25.5 ppb, Home+Work=24.7 ppb, Monitor IDW=13.0 ppb; NO_2 LUR Home=2.8 ppb, Home+Work=2.5 ppb; $PM_{2.5}$ Monitor IDW= 1.8 $\mu g/m^3$.

		Percentage change in personal measurements for IQR change in:		
Personal Pollutant Concentration (dependent)		**LUR Home (Postal)**	**LUR Home+Work (Postal)**	**Monitor-based IDW (Monthly)**
NO	Unadjusted	61 (41, 83)	68 (48, 91)	41 (29, 53)
	Adjusted	52 (35, 71)	59 (41, 79)	34 (24, 46)
NO_2[1]	Unadjusted	7 (-1, 15)	11 (3, 19)	--
	Adjusted	8 (0, 16)	11 (4, 19)	--
Absorbance	Unadjusted	--	--	18 (7, 31)
	Adjusted	--	--	14 (5, 24)
$PM_{2.5}$	Unadjusted	--	--	12 (0, 24)
	Adjusted	--	--	12 (1, 24)

[1] NO_2 models all use *annual* LUR model. NO uses monthly model.

Activity patterns comparisons to CHAPS

Table E.37 CHAPS – PHAIR Study populations, Descriptive Results for Categorical Variables

Questionnaire Variable	Level	PHAIR Population Vancouver (n=129)	CHAPS Population Vancouver & St. Johns, NB (n=168)	CHAPS Population Vancouver only (n=103)
Is Pregnant? Y/N	No		161 (96%)	99 (96%)
	Yes	129 (100%)	7 (4%)	4 (4%)
Region	Vancouver, BC	129 (100%)	103 (61%)	103 (100%)
	St John's, NB		65 (39%)	
Education Level	Not specified	2 (2%)		
	High School		86 (51%)	44 (43%)
	Trades or College	7 (5%)	32 (19%)	19 (18%)
	University	51 (40%)	34 (20%)	27 (26%)
	University >Masters	69 (53%)	16 (10%)	13 (13%)
Number of Other Children	None	85 (66%)	106 (63%)	67 (65%)
	1	44 (34%)	27 (16%)	14 (14%)
	2		23 (14%)	15 (15%)
	3 or more		12 (7%)	7 (7%)
Is Worker? Y/N	No	12 (9%)	41 (24%)	27 (26%)
	Yes	117 (91%)	127 (76%)	76 (74%)
Worked on Sample Day? Y/N	No	32 (25%)	90 (54%)	54 (52%)
	Yes	97 (75%)	78 (46%)	49 (48%)
Season	Winter	40 (31%)	51 (30%)	35 (34%)
	Spring	50 (39%)	43 (26%)	33 (32%)
	Summer	21 (16%)	67 (40%)	28 (27%)
	Fall	18 (14%)	7 (4%)	7 (7%)

Table E.38 PHAIR-CHAPS comparisons between populations for workers and non-workers

		PHAIR (n=129)		CHAPS (n=168)	
Questionnaire Variable	**Level**	**Non-worker**	**Worker**	**Non-worker**	**Worker**
Is Pregnant? Y/N	No			39 (95%)	122 (96%)
	Yes	12 (100%)	117 (100%)	2 (5%)	5 (4%)
Region	Vancouver, BC	12 (100%)	117 (100%)	27 (66%)	76 (60%)
	St John's, NB			14 (34%)	51 (40%)
Education Level	Not specified	1 (8%)	1 (1%)		
	High School			26 (63%)	60 (47%)
	Trades or College	1 (8%)	6 (5%)	6 (15%)	26 (20%)
	University	2 (17%)	49 (42%)	6 (15%)	28 (22%)
	University >Masters	8 (67%)	61 (52%)	3 (7%)	13 (10%)
Number of Other Children	None	3 (25%)	82 (70%)	28 (68%)	78 (61%)
	1	9 (75%)	35 (30%)	5 (12%)	22 (17%)
	2			7 (17%)	16 (13%)
	3 or more			1 (2%)	11 (9%)
Worked on Sample Day? Y/N	No	12 (100%)	20 (17%)	41 (100%)	49 (39%)
	Yes		97 (83%)		78 (61%)
Season	Winter	5 (42%)	35 (30%)	14 (34%)	37 (29%)
	Spring	3 (25%)	47 (40%)	15 (37%)	28 (22%)
	Summer	2 (17%)	19 (16%)	11 (27%)	56 (44%)
	Fall	2 (17%)	16 (14%)	1 (2%)	6 (5%)

Table E.39 Activity Pattern differences for Vancouver women only (CHAPS)

	Comparisons		PHAIR (n=129 samples, 62 women)		CHAPS (n=103, Vancouver ONLY)	
Variables	**Prob>|t| Equal Variance** [1]		**Mean (95% CI)**	**(Min-Max)**	**Mean (95% CI)**	**(Min-Max)**
Original Data:						
Indoors Home		.	67.1% (64.8% - 69.4%)	(41%-96%)	63.8% (60.5% - 67.2%)	(31%-100%)
Indoors Work		.	17.3% (15.1% - 19.6%)	(0%-41%)	15.7% (12.3% - 19.0%)	(0%-50%)
Indoors Other	**	0.0012	6.5% (5.5% - 7.5%)	(0%-24%)	**10.3% (8.0% - 12.5%)**	**(0%-43%)**
Outdoors Near Home		.	0.5% (0.3% - 0.8%)	(0%-7%)	0.6% (0.2% - 1.0%)	(0%-15%)
Outdoors Away	*	0.0139	1.1% (0.7% - 1.5%)	(0%-12%)	**2.4% (1.3% - 3.5%)**	**(0%-33%)**
Data: Transit Car	**	0.0014	3.6% (3.0% - 4.1%)	(0%-14%)	**5.8% (4.4% - 7.1%)**	**(0%-49%)**
Transit Bus		.	0.9% (0.6% - 1.2%)	(0%-8%)	0.6% (0.3% - 0.9%)	(0%-9%)
Walk	**	<.0001	**2.7% (2.3% - 3.2%)**	**(0%-13%)**	0.7% (0.3% - 1.0%)	(0%-9%)
Bike		.	0.3% (0.1% - 0.5%)	(0%-7%)	0.1% (0.0% - 0.3%)	(0%-3%)
Recoded Data:						
Home (Near/At)		.	67.6% (65.3% - 70.0%)	(41%-97%)	64.4% (61.1% - 67.7%)	(31%-100%)
Work		.	17.3% (15.1% - 19.6%)	(0%-41%)	15.7% (12.3% - 19.0%)	(0%-50%)
Motorized Transit	**	0.0036	4.5% (4.0% - 5.0%)	(0%-14%)	**6.4% (5.1% - 7.7%)**	**(0%-49%)**
Outdoors All-Bike & Walk	*	0.0299	**4.6% (3.9% - 5.3%)**	**(0%-18%)**	3.2% (2.1% - 4.3%)	(0%-33%)
Transit All		.	7.5% (6.9% - 8.0%)	(0%-18%)	7.2% (5.9% - 8.5%)	(0%-49%)
Outdoors		.	1.6% (1.1% - 2.1%)	(0%-12%)	2.4% (1.3% - 3.5%)	(0%-33%)
Indoors		.	90.9% (90.2% - 91.7%)	(73%-98%)	89.8% (87.9% - 91.6%)	(45%-100%)
Subject Age			32 (32 - 33)	(23-40)	31 (30 - 33)	(17-45)
Total Hours of Activity Log Time	**	<.0001	**47 (47 - 48)**	(43-51)	24 (24 - 24)	(24-24)

[1] p<0.01=** , 0.01-0.1=*, p>0.1 blank

Table E.40 PHAIR-CHAPS Comparisons of Activity Log Data, Age and Sample Time: Means and T-tests results

	Comparisons			PHAIR (n=129)		CHAPS Vancouver & St. Johns (n=168)	
Variables		**Prob>|t| Equal Variance [1]**	**Differ-ences in Means**	**Mean (95% CI)**	**(Min-Max)**	**Mean (95% CI)**	**(Min-Max)**
Original Data:							
Indoors Home	*	0.0367	↑ PHAIR	67.1% (64.8% - 69.4%)	(41%-96%)	63.2% (60.5% - 65.9%)	(0%-100%)
Indoors Work				17.3% (15.1% - 19.6%)	(0%-41%)	14.9% (12.3% - 17.5%)	(0%-50%)
Indoors Other	**	<.0001	↑ CHAPS	6.5% (5.5% - 7.5%)	(0%-24%)	11.8% (9.9% - 13.7%)	(0%-61%)
Outdoors Near Home				0.5% (0.3% - 0.8%)	(0%-7%)	1.0% (0.4% - 1.6%)	(0%-42%)
Outdoors Away	*	0.0124	↑ CHAPS	1.1% (0.7% - 1.5%)	(0%-12%)	2.4% (1.5% - 3.3%)	(0%-33%)
Data: Transit Car	**	0.0025	↑ CHAPS	3.6% (3.0% - 4.1%)	(0%-14%)	5.5% (4.5% - 6.4%)	(0%-49%)
Transit Bus	*	0.0604	↑ PHAIR	0.9% (0.6% - 1.2%)	(0%-8%)	0.6% (0.3% - 0.8%)	(0%-9%)
Walk	**	<.0001	↑ PHAIR	2.7% (2.3% - 3.2%)	(0%-13%)	0.6% (0.4% - 0.9%)	(0%-10%)
Bike	*	0.0691	↑ PHAIR	0.3% (0.1% - 0.5%)	(0%-7%)	0.1% (0.0% - 0.2%)	(0%-3%)
Recoded Data:							
Home (Near/At)	*	0.0665	↑ PHAIR	67.6% (65.3% - 70.0%)	(41%-97%)	64.2% (61.4% - 66.9%)	(0%-100%)
Work				17.3% (15.1% - 19.6%)	(0%-41%)	14.9% (12.3% - 17.5%)	(0%-50%)
Motorized Transit	*	0.0112	↑ CHAPS	4.5% (4.0% - 5.0%)	(0%-14%)	6.0% (5.1% - 7.0%)	(0%-49%)
Outdoors All-Bike & Walk	*	0.0202	↑ PHAIR	4.6% (3.9% - 5.3%)	(0%-18%)	3.1% (2.2% - 4.1%)	(0%-33%)
Transit All				7.5% (6.9% - 8.0%)	(0%-18%)	6.7% (5.8% - 7.7%)	(0%-49%)
Outdoors				1.6% (1.1% - 2.1%)	(0%-12%)	2.4% (1.5% - 3.3%)	(0%-33%)
Indoors				90.9% (90.2% - 91.7%)	(73%-98%)	89.9% (88.3% - 91.4%)	(45%-100%)
Subject Age				32 (32 - 33)	(23-40)	31 (30 - 33)	(17-45)
Total Hours of Activity Log Time	**	<.0001	↑ PHAIR	47 (47 - 48)	(43-51)	24 (24 - 24)	(24-24)

1 p<0.01=** , 0.01-0.1=*, p>0.1 blank

Table E.41 Compare CHAPS Workers and Non-workers (Women aged 18-45) T-tests and Means

Variable	Differences p-value[1], direction			Mean (95% CI)	(Min-Max)	Mean (95% CI)	(Min-Max)
				CHAPS(n=168)			
				Non-worker (n=41)		Worker (n=127)	
Original Data:							
Indoors Home	**	0.0001	↑ Non-worker	72.3% (67.3% - 77.3%)	(45.1%-100.0%)	60.2% (57.2% - 63.3%)	(0.0%-100.0%)
Indoors Work	**	<.0001	↑ Worker	0.0% (0.0% - 0.0%)	(0.0%-0.0%)	19.7% (16.7% - 22.7%)	(0.0%-50.3%)
Indoors Other	**	0.0003	↑ Non-worker	17.9% (13.4% - 22.3%)	(0.0%-43.4%)	9.8% (7.9% - 11.8%)	(0.0%-61.0%)
Outdoors Near Home				1.6% ((0.6%) - 3.7%)	(0.0%-42.0%)	0.8% (0.3% - 1.2%)	(0.0%-18.1%)
Outdoors Away				1.7% (0.5% - 2.9%)	(0.0%-16.7%)	2.7% (1.5% - 3.8%)	(0.0%-33.3%)
Data: Transit Car				4.6% (2.1% - 7.1%)	(0.0%-49.0%)	5.7% (4.7% - 6.8%)	(0.0%-40.3%)
Transit Bus	*	0.0237	↑ Non-worker	1.1% (0.5% - 1.6%)	(0.0%-5.6%)	0.4% (0.1% - 0.7%)	(0.0%-9.4%)
Walk				0.9% (0.3% - 1.5%)	(0.0%-8.7%)	0.5% (0.3% - 0.8%)	(0.0%-10.4%)
Bike				0.0% (0.0% - 0.0%)	(0.0%-0.0%)	0.1% (0.0% - 0.2%)	(0.0%-3.5%)
Recoded Data:							
Home (Near/At)	**	<.0001	↑ Non-worker	73.8% (69.0% - 78.7%)	(47.9%-100.0%)	61.0% (57.9% - 64.1%)	(0.0%-100.0%)
Work	**	<.0001	↑ Worker	0.0% (0.0% - 0.0%)	(0.0%-0.0%)	19.7% (16.7% - 22.7%)	(0.0%-50.3%)
Motorized Transit				5.7% (3.2% - 8.2%)	(0.0%-49.0%)	6.1% (5.1% - 7.2%)	(0.0%-40.3%)
Outdoors All-Bike & Walk				2.6% (1.3% - 3.9%)	(0.0%-16.7%)	3.3% (2.2% - 4.5%)	(0.0%-33.3%)
Transit All				6.6% (4.0% - 9.1%)	(0.0%-49.0%)	6.8% (5.8% - 7.8%)	(0.0%-40.3%)
Outdoors				1.7% (0.5% - 2.9%)	(0.0%-16.7%)	2.7% (1.5% - 3.8%)	(0.0%-33.3%)
Indoors				90.2% (86.7% - 93.7%)	(45.1%-100.0%)	89.8% (88.1% - 91.4%)	(44.8%-100.0%)
Subject Age				30 (27 - 32)	(18-45)	32 (30 - 33)	(17-45)
Total Hours of Sample	*same*			24 (24 - 24)	(24-24)	24 (24 - 24)	(24-24)

1 p<0.01=** , 0.01-0.1=*, p>0.1 blank

Table E.42 Compare PHAIR Workers and Non-workers T-tests and Means

Variable	Differences p-value[1], direction		Mean (95% CI)	(Min-Max)	Mean (95% CI)	(Min-Max)
			PHAIR (n=129)			
			Non-worker (n=12)		*Worker (n=117)*	
Original Data:						
Indoors Home	** <.0001	↑ Non-worker	84.7% (81.2% - 88.2%)	(75.0%-95.9%)	65.3% (63.0% - 67.6%)	(40.6%-94.1%)
Indoors Work	** <.0001	↑ Worker	0.0% (0.0% - 0.0%)	(0.0%-0.0%)	19.1% (16.8% - 21.4%)	(0.0%-41.2%)
Indoors Other	.	n.s.	6.2% (3.9% - 8.6%)	(0.5%-12.5%)	6.5% (5.5% - 7.6%)	(0.0%-24.5%)
Outdoors Near Home	.	n.s.	0.3% ((0.0%) - 0.7%)	(0.0%-1.6%)	0.6% (0.3% - 0.8%)	(0.0%-7.4%)
Outdoors Away	* 0.02	↑ Non-worker	2.6% (0.2% - 4.9%)	(0.0%-11.9%)	0.9% (0.5% - 1.3%)	(0.0%-11.6%)
Data: Transit Car	.	n.s.	2.2% (0.6% - 3.8%)	(0.0%-6.3%)	3.7% (3.1% - 4.3%)	(0.0%-14.2%)
Transit Bus	.	n.s.	0.8% ((0.2%) - 1.8%)	(0.0%-4.2%)	0.9% (0.6% - 1.2%)	(0.0%-8.1%)
Walk	.	n.s.	3.2% (1.6% - 4.7%)	(0.5%-8.9%)	2.7% (2.2% - 3.2%)	(0.0%-13.0%)
Bike	.	n.s.	0.0% (0.0% - 0.0%)	(0.0%-0.0%)	0.3% (0.1% - 0.5%)	(0.0%-7.2%)
Recoded Data:						
Home (Near/At)	** <.0001	↑ Non-worker	85.0% (81.5% - 88.5%)	(75.0%-95.9%)	65.8% (63.5% - 68.2%)	(40.6%-96.9%)
Work	** <.0001	↑ Worker	0.0% (0.0% - 0.0%)	(0.0%-0.0%)	19.1% (16.8% - 21.4%)	(0.0%-41.2%)
Motorized Transit	* 0.07	↑ Worker	3.0% (1.6% - 4.4%)	(0.0%-6.3%)	4.6% (4.1% - 5.2%)	(0.0%-14.2%)
Outdoors All-Bike & Walk	.	n.s.	6.1% (3.3% - 8.8%)	(1.0%-13.4%)	4.4% (3.7% - 5.1%)	(0.0%-17.6%)
Transit All	.	n.s.	6.2% (4.3% - 8.0%)	(2.1%-9.9%)	7.6% (7.0% - 8.2%)	(0.0%-17.9%)
Outdoors	* 0.09	↑ Non-worker	2.9% (0.7% - 5.2%)	(0.0%-11.9%)	1.5% (1.0% - 2.0%)	(0.0%-11.6%)
Indoors	.	n.s.	90.9% (88.3% - 93.5%)	(83.9%-97.9%)	90.9% (90.1% - 91.8%)	(72.9%-97.9%)
Subject Age	* 0.08	↑ Non-worker	34 (33 - 36)	(31-38)	32 (32 - 33)	(23-40)
Total Hours of Sample			48 (47 - 48)	(47-49)	47 (47 - 48)	(43-51)

1 p<0.01=** , 0.01-0.1=*, p>0.1 blank

Table E.43 Differences in Continuous Variables -Workers & Non-Workers

Variable	*Differences p-value[1], direction*	Mean (95% CI)	(Min-Max)	Mean (95% CI)	(Min-Max)
			CHAPS		
		Non-worker (n=41)		***Worker (n=127)***	
Subject Age	*n.s*	30 (27 - 32)	(18-45)	32 (30 - 33)	(17-45)
Total Hours of Sample	*same*	24 (24 - 24)	(24-24)	24 (24 - 24)	(24-24)
			PHAIR		
		Non-worker (n=12)		***Worker (n=117)***	
Subject Age	* 0.0839 ↑ Non-worker	34 (33 - 36)	(31-38)	32 (32 - 33)	(23-40)
Total Hours of Sample	*n.s.*	48 (47 - 48)	(47-49)	47 (47 - 48)	(43-51)

1 p<0.01=** , 0.01-0.1=*, p>0.1 blank

Table E.44 Summary of T-test comparisons Workers-Non Workers

Variable	***PHAIR Worker-Non Worker***		***CHAPS Worker-Non Worker***	
	Differences p-value[1], direction		*Differences p-value, direction*	
Original Data: Indoors Home	** <.0001	↑ Non-worker	** 0.0001	↑ Non-worker
Original Data: Indoors Work	** <.0001	↑ Worker	** <.0001	↑ Worker
Original Data: Indoors Other			** 0.0003	↑ Non-worker
Original Data: Outdoors Near Home				
Original Data: Outdoors Away	* 0.0155	↑ Non-worker		
Original Data: Transit Car				
Original Data: Transit Bus			* 0.0237	↑ Non-worker
Original Data: Walk				
Original Data: Bike				
Recoded: Home (Near)	** <.0001	↑ Non-worker	** <.0001	↑ Non-worker
Recoded: Work	** <.0001	↑ Worker	** <.0001	↑ Worker
Recoded: Motorized Transit	* 0.0711	↑ Worker		
Recoded: Outdoors All-Bike & Walk				
Recoded: Transit All				
Recoded: Outdoors	* 0.0865	↑ Non-worker		
Recoded: Indoors				
Subject Age	* 0.0839	↑ Non-worker		
Total Hours of Sample				

1 p<0.01=** , 0.01-0.1=*, p>0.1 blank

Changes in Activity Patterns of PHAIR Study Participants (pregnant women) by Season and Trimester

Table E.45 Activity Log Means by Season

Variable Description	*Prob>|t| Equal Variances*		*Differences in Means*	*Mean (95% CI) Summer n=54*	*(Min-Max) Summer*	*Mean (95% CI) Winter n=75*	*(Min-Max) Winter*
Original Data:							
Indoors Home		.	.	66.9% (63.4% - 70.5%)	(40.6%-93.8%)	67.2% (64.2% - 70.3%)	(44.1%-95.9%)
Indoors Work		.	.	16.8% (13.0% - 20.6%)	(0.0%-38.5%)	17.7% (14.8% - 20.7%)	(0.0%-41.2%)
Indoors Other	*	0.0724	↑ Winter	5.5% (4.3% - 6.7%)	(0.0%-19.8%)	7.2% (5.8% - 8.6%)	(0.0%-24.5%)
Outdoors Near Home	**	0.0011	↑ Summer	1.0% (0.5% - 1.5%)	(0.0%-7.4%)	0.2% (0.1% - 0.4%)	(0.0%-3.3%)
Outdoors Away	**	<.0001	↑ Summer	2.2% (1.3% - 3.0%)	(0.0%-11.9%)	0.3% (0.1% - 0.5%)	(0.0%-5.3%)
Data: Transit Car		.	.	3.8% (2.9% - 4.6%)	(0.0%-14.2%)	3.4% (2.7% - 4.2%)	(0.0%-13.5%)
Transit Bus	*	0.0111	↑ Winter	0.5% (0.2% - 0.8%)	(0.0%-4.1%)	1.2% (0.8% - 1.6%)	(0.0%-8.1%)
Walk		.	.	2.9% (2.2% - 3.7%)	(0.0%-13.0%)	2.6% (2.0% - 3.1%)	(0.0%-9.9%)
Bike		.	.	0.4% (0.0% - 0.8%)	(0.0%-7.2%)	0.1% ((0.0%) - 0.3%)	(0.0%-5.3%)
Recoded Data:							
Home (Near/At)		.	.	67.9% (64.2% - 71.6%)	(40.6%-96.9%)	67.4% (64.4% - 70.5%)	(44.1%-95.9%)
Work		.	.	16.8% (13.0% - 20.6%)	(0.0%-38.5%)	17.7% (14.8% - 20.7%)	(0.0%-41.2%)
Motorized Transit		.	.	4.3% (3.4% - 5.1%)	(0.0%-14.2%)	4.6% (3.9% - 5.3%)	(0.0%-13.5%)
Outdoors All-Bike & Walk	**	<.0001	↑ Summer	6.5% (5.3% - 7.7%)	(0.0%-17.6%)	3.2% (2.5% - 3.8%)	(0.0%-13.0%)
Transit All		.	.	7.7% (6.7% - 8.6%)	(1.0%-16.8%)	7.3% (6.5% - 8.1%)	(0.0%-17.9%)
Outdoors	**	<.0001	↑ Summer	3.1% (2.2% - 4.1%)	(0.0%-11.9%)	0.5% (0.3% - 0.7%)	(0.0%-5.3%)
Indoors	**	<.0001	↑ Winter	89.2% (87.8% - 90.6%)	(72.9%-97.4%)	92.2% (91.4% - 93.0%)	(82.1%-97.9%)

Table E.46 Activity Log Means by Trimester of Pregnancy

Variable Description	Anova P-value	Highest Mean	1st Trimester n=12 Mean (95% CI)	2nd Trimester n=62 Mean (95% CI)	3rd Trimester n=55 Mean (95% CI)
Original : Indoors Home	* 0.0365	3rd Trimester ↑	58.6% (53.8% - 63.4%)	66.8% (63.4% - 70.3%)	69.3% (65.8% - 72.8%)
Original : Indoors Work	* 0.0990	1st Trimester ↑	24.3% (19.4% - 29.1%)	17.7% (14.4% - 21.1%)	15.4% (11.7% - 19.1%)
Original : Indoors Other	.		9.4% (4.4% - 14.4%)	6.5% (5.2% - 7.8%)	5.9% (4.4% - 7.3%)
Original : Outdoors Near Home	* 0.0176	3rd Trimester ↑	0.0% (0.0% - 0.0%)	0.3% (0.0% - 0.6%)	0.9% (0.5% - 1.3%)
Original : Outdoors Away	** 0.0055	3rd Trimester ↑	0.0% (0.0% - 0.0%)	0.6% (0.3% - 1.0%)	1.8% (1.0% - 2.6%)
Original : Transit Car	.		4.4% (2.1% - 6.7%)	3.6% (2.8% - 4.4%)	3.3% (2.5% - 4.2%)
Original : Transit Bus	.		1.0% (0.0% - 2.1%)	1.0% (0.6% - 1.4%)	0.8% (0.4% - 1.2%)
Original : Walk	.		1.8% (0.9% - 2.8%)	3.1% (2.4% - 3.8%)	2.5% (1.8% - 3.2%)
Original : Bike	.		0.4% ((0.3%) - 1.2%)	0.3% ((0.0%) - 0.5%)	0.2% ((0.1%) - 0.5%)
Recoded: Home (Near)	* 0.0218	3rd Trimester ↑	58.6% (53.8% - 63.4%)	67.1% (63.7% - 70.6%)	70.2% (66.6% - 73.8%)
Recoded: Work	* 0.0990	1st Trimester ↑	24.3% (19.4% - 29.1%)	17.7% (14.4% - 21.1%)	15.4% (11.7% - 19.1%)
Recoded: Motorized Transit	.		5.4% (3.5% - 7.4%)	4.6% (3.9% - 5.4%)	4.1% (3.3% - 4.9%)
Recoded: Outdoors All-Bike & Walk	* 0.0335	3rd Trimester ↑	2.3% (1.0% - 3.5%)	4.3% (3.4% - 5.3%)	5.4% (4.2% - 6.5%)
Recoded: Transit All	.		7.7% (6.0% - 9.4%)	8.0% (7.1% - 8.9%)	6.8% (5.9% - 7.7%)
Recoded: Outdoors	** 0.0003	3rd Trimester ↑	0.0% (0.0% - 0.0%)	1.0% (0.5% - 1.4%)	2.7% (1.7% - 3.6%)
Recoded: Indoors	.		92.3% (90.6% - 94.0%)	91.1% (90.0% - 92.1%)	90.5% (89.3% - 91.8%)

Figure E.7 Scatter plot and regression line for weeks of pregnancy and time spent at home

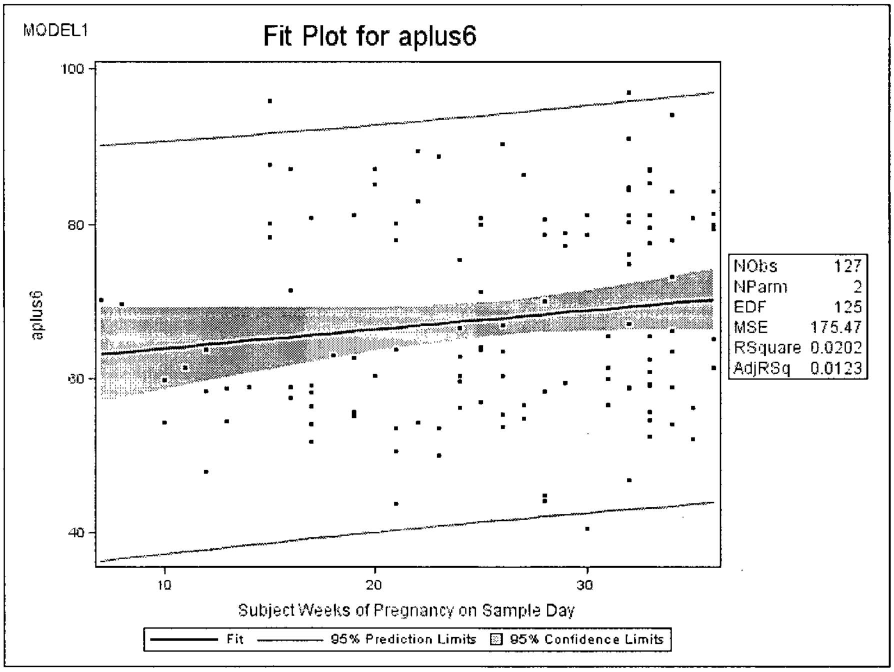


Table E.47 Predictive Mixed Models for Activity Time Spent at/near Home

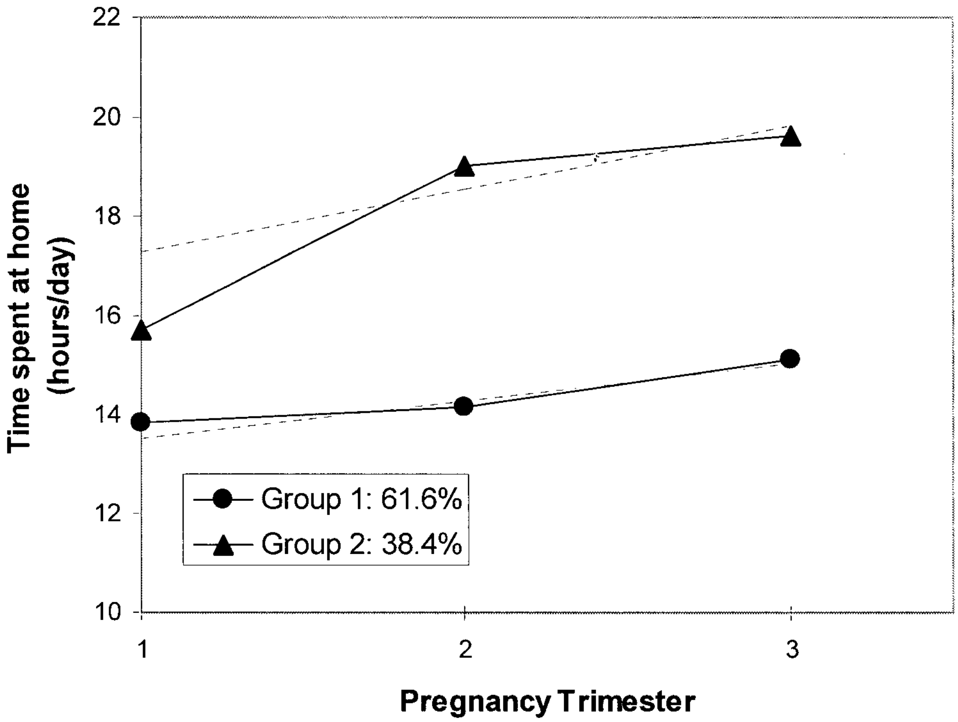
All Models w/ Subject included (random effect)	Variance Component (95% Confidence Limits)		% Variance Explained (compared to baseline)		
Fixed effects **Models for Time spent at home (dependent)**	**Within Subject (σ_{ws})**	**Between Subject (σ_{BS})**	**σ_{ws}**	**σ_{BS}**	**Total**
Baseline	85.8 (62 ,126)	96.9 (60 ,184)	.	.	.
Weeks of Pregnancy	75.1 (54 ,111)	107.3 (68 ,195)	12	-11	0
Other children	85.7(62 ,126)	85.7 (52 ,169)	0	12	6
Income	85.8 (62 ,125)	75.1 (44 ,157)	0	23	12
Worker	85.5 (62 ,125)	65.0 (37,142)	0	33	18
Weeks + Other children+ Income + Worker	75.3 (55 ,111)	53.9 (30 ,126)	12	44	29

Table E.48 Effect estimates for models predicting time (hours/day) spent at/near home (dependent)

	Mean Intercept[1]	Effect Estimate ($CL_{5\%}$, $CL_{95\%}$) Predicted change in hours/day for effect	p-value[2]
Model 1 (Weeks Only)	14.3 (12.7 , 15.9)		
Weeks of Pregnancy		0.1 (0.0 , 0.1)	0.0065
Model 2 (Final Model)	13.7 (11.9 ,15.5)		
Income: <40k		2.60 (0.6 ,4.6)	0.0131
Income: 40-100k		1.92 (0.6 ,3.2)	0.0043
Income: >100k		Reference	
Non-Worker		3.47 (1.4 ,5.5)	0.0013
Other children=No		-1.48 (-2.8 ,-0.1)	0.0313
Weeks of Pregnancy		0.08 (0.0 ,0.1)	0.0067

[1] All models included subject as a random effect (random intercept) to control for within subject correlation, so the mean intercept is the population mean of all individual (subject-specific) intercepts.
[2] P-value from mixed effect regression model fixed effect estimate.

Figure E.8 Trajectory model output-Time spent at home by pregnancy trimester, 2 group model



Appendix F Air Quality Recommendations for Urban and Rural Land Development in BC and Supporting Documentation

Ministry of Environment

Environmental Best Management Practices for Urban and Rural Land Development in British Columbia: Supporting Information (Air Quality)

Recommendations

Specific concern is focused on the siting of "sensitive land uses":

- buildings where people spend large amounts of time – seven to eight hours per day; and
- buildings that primarily house vulnerable populations (infants, children, pregnant women, the elderly and those who are ill).

Buildings: Locating the Site

Recommendations to minimize the health impacts of air pollution associated with proximity to major roads include:

1. **Setbacks:** 150 metre (500 feet) setback from "busy roads[1]" for sensitive land uses (buildings such as schools, hospitals, long-term care facilities and residences).
2. **Truck Routes**: Special consideration should be applied for buildings located on major truck routes. Avoiding development of sensitive land uses on truck routes or using additional setbacks near truck routes or truck distribution centers is recommended. Elevated air pollutant concentrations are measurable as far as 750 metres from truck routes. Heavy-duty trucks generally emit larger quantities of air pollutants, including diesel-exhaust particulate, a probable[2] human carcinogen, and likely the most harmful vehicle-related pollutant.

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[1] Busy Roads (Definition): A busy road is defined as a road with greater than 15,000 vehicles/day based on annual daily average traffic counts.

[2] Group 2A – International Agency for Research on Cancer. www.iarc.org

3. **Street Canyons:** Avoid locating buildings within street canyons (Table 3: Street Canyon Definitions), which can trap air pollution. To avoid creating street canyons, stagger buildings that are perpendicular to the predominant wind direction or site high-rise buildings on only one side of the street (when perpendicular to the predominant wind direction).

Site (Outdoor) Considerations

4. **Trees:** On a local scale, trees have little impact on air quality, although on a city-wide, regional scale, they increase carbon dioxide conversion to oxygen and promote cooling. Trees are important from a site-quality and greenspace perspective, however, and should still be considered a valuable feature of land development.

Building Construction/Design

5. **Idling/Loading Dock Locations**: Air intakes for buildings must not be located near loading docks or where vehicles are often idling. Similarly, building intakes should not be located on a side of a building near a busy traffic corridor where vehicles may be idling in traffic congestion. This will help avoid indoor air quality problems.
6. **Filters:** Where proximity to traffic is unavoidable, the use of high-efficiency particulate air (HEPA) filters (portable single-room air cleaners or centralized filtration for buildings with mechanical ventilation) for vulnerable populations will reduce exposure to particulate air pollution. However, HEPA filters will not reduce exposure to gaseous air pollutants (e.g. CO, NO_x, SO_2), and require maintenance and increased energy to operate.

Supporting Information

Introduction and Rationale

According to a growing body of scientific literature, people living near freeways and major roads (roadways) have a higher risk of developing (or worsening) health problems such as asthma, chronic bronchitis, emphysema, pneumonia and heart disease. Motor vehicles emit at least 40 different air pollutants, usually concentrated within 150 metres (500 feet) of freeways and busy roadways. The research points to a need for increased awareness of the public health concerns associated with roadway proximity in creating land-use policy and environmental/air quality management programs (1).

Existing air quality management programs related to motor vehicles generally focus on reducing the emissions from individual vehicles (e.g. inspection-and-maintenance programs such as AirCare, in the Lower Fraser Valley) and on promotion of programs to reduce the total number of vehicle-km travelled. However, less attention has been placed on reducing population exposures to aggregate traffic sources. The above best management practices are intended to provide general advice regarding building placement (including recommended setbacks) and general land use that will reduce exposures and health risks associated with traffic proximity. They can be implemented along with existing, more traditional air quality management strategies (for example, those focusing on emissions reduction) to reduce the public health impacts arising from vehicle-related air pollution. "Sensitive land uses" refer to those that are predominantly populated by susceptible populations (infants, children, pregnant women, the elderly and those who are ill) and includes facilities such as schools, hospitals, long-term care facilities and residences. As additional air quality management tools and regulations are implemented or changes in emissions occur, it is advisable to periodically review this BMP.

This document reviews existing guidelines that have been implemented in other jurisdictions, along with the evidence that higher concentrations of hazardous air pollutants exist near major roadways. It defines a "major roadway," which roadways should also be considered as street canyons, and the specific levels of traffic that lead to concern. Sources for information on characterizing roads in British Columbia are listed. In addition, the information regarding studies of health effects in relation to roadway proximity is summarized.

Existing Guidelines: Setbacks

To date, only school siting in relation to traffic-related air pollution has been incorporated into legislation. (See a 2005 review entitled *Fifty State Survey of School Siting Laws, Regulations and Policies* (2) by Rhode Island Legal Services with funding from the US EPA. It "surveys state laws, regulations and policy guidance document regarding the siting of schools".) With respect to school siting and air pollution sources, the California legislation (described below) is the most strict and explicit regarding school proximity to traffic. However, at least 10 other states have statements (in legislation) to encourage minimizing exposure to air pollution in school siting.

On September 11, 2003, the State of California passed Senate Bill No. 352 (3), which amends previous legislation on planning and siting public schools. Previous California legislation (Section 17213 of the Education Code and Public Resources code 21151.8) (4;5) essentially required that school sites be selected such that:

a. no pollution-generating facilities (broadly written to specify any hazardous air pollution source) be situated within a ¼-mile radius of any school site; or
b. corrective measures are being used to mitigate all hazardous emissions; or
c. there are no health risks posed to school occupants from the identified facilities.

Bill 352 amends the previous legislation to include "freeways and other busy traffic corridors, large agricultural operations, and rail yards" in the definition of pollution sources. Furthermore, the legislation attempts to prohibit the location of any school site within 500 feet (150 metres) of a freeway or other busy traffic corridor. In the State of California legislation, the definitions of a "freeway or other busy traffic corridor" are "roadways that, on an average day, have traffic in excess of 50,000 vehicles in a rural area … or 100,000 vehicles in an urban area."

The justification for this amendment to the existing legislation pertains to the following (excerpts from the legislation):

a. Higher levels of air pollutants have been detected near freeways and busy traffic corridors; this pollution has been associated with acute health effects (including asthma exacerbation) and negatively impacts the ability of children to learn.

b. Cars and trucks emit at least 40 different air toxics/contaminants; levels are generally concentrated within 500 feet (150 metres) of freeways and busy roadways.
c. A disproportionate number of economically disadvantaged pupils may be attending schools that are close to busy roads; these students are at an increased risk of developing chronic health conditions caused or exacerbated by exposure to traffic-related pollutants.
d. The intent of the legislation is to protect school children from the negative health effects of freeway traffic, as well as other industrial pollution sources.

The California EPA also produced an informational guide on air quality and land use issues entitled "Air Quality and Land Use Handbook: A Community Health Perspective" (6). This document is an excellent resource to community members seeking to understand the issues around air pollution and health in their communities. In the California recommendations, locating sensitive land uses was also addressed for other community air pollution sources e.g. dry cleaners, refineries, railyards, ports, in addition to vehicle traffic-related air pollution. While this British Columbia Best Management Practice is focussed on traffic proximity, it is nevertheless important to avoid locating sensitive land uses near other pollution sources.

Dispersion of Pollutants from Roads / across Urban Areas

Vehicles and motor vehicle traffic generate a complex mixture of air pollutants that can vary according to factors such as: the age of the vehicle, type of fuel, engine type, speed of travel, roadway conditions and density of traffic. In general, the concentrations of pollutants decrease away from sources (highways, major roadways) as pollutants are transported and dispersed by wind and turbulence. The amount of transport and dispersion of pollutants is affected by meteorological conditions (weather), temperature, topography and vehicle traffic/movement.

Several studies have measured pollutant concentrations and distributions at different locations in urban and rural areas. Different pollution metrics (indicators) vary when measured at various distances from highways. These are:

- $PM_{2.5}$ (PM or "particulate matter" refers to very small gas and liquid particles in the atmosphere. $PM_{2.5}$ is 2.5 micrometres or smaller in diameter.);
- ultrafine particles (less than 0.1 micrometres in diameter);
- particle number concentrations (the number of particles per volume of air);
- carbon monoxide (CO);

- black smoke (a measure of elemental carbon);
- nitrogen dioxide (NO_2); and
- nitrogen oxides (NO_x).

In general, $PM_{2.5}$ does not decrease much with growing distance from major roads because motor vehicles are not the major source of $PM_{2.5}$ – and usually $PM_{2.5}$ levels do not vary across small distances. For this reason, pollution due to motor vehicles is better represented by NO_2 (or NO_x), particle number concentrations, or ultrafine particles. All these metrics, as well as black smoke, decrease significantly at increased distances from major roads.

Specific Measurement of Traffic Pollutants with Distance from Roads

The World Health Organization (7) recently summarized over 15 different studies in which pollutant concentrations measured at traffic sites were a factor of 1.2 to 2.3 higher than urban-background sites in the same cities. Clearly, pollution concentrations are generally elevated at traffic sites. The gradient of decline of the pollutant concentration when moving away from the traffic site varies with pollutant; however, there are some overall similarities.

As shown in Table 1, various studies reported that black smoke decreased by 80-55% in the first 150 metres away from the road. The black smoke then stabilized, reaching urban-background levels at 150-200 metres away (Figure 1: Black Smoke Concentration Reduction with Distance from Major Roads). In contrast, $PM_{2.5}$ concentrations decreased by only 20-10% in the first 200 metres from the road, with no further decrease at greater distances (Table 2), (Figure 2: $PM_{2.5}$ Concentration with Distance from Major Roads).

Measured NO_2 concentrations decreased by 30-70% in the first 150 metres from the roadside. They then reached urban-background levels by 150-300 metres from the roadside (Figure 3: NO_2 Concentration Reduction with Distance from Major Roads). Particle number concentrations generally had a 50% reduction at 150 metres from roads in several different wind conditions. In addition, the particle number distributions (the numbers of differently sized particles in the air) at 150 metres were comparable to urban background, indicating that little contribution remains (at 150 metres) from vehicle traffic (7).

Several studies have found higher concentrations and gradients near highways with a greater percentage (than normal) of diesel truck traffic – specifically black smoke and ultrafine particles (8). Particle concentrations ($PM_{2.5}$) decrease only slightly with increased distance from busy roads. However, particle number concentrations decrease much more significantly and provide a better measure of decreasing traffic-source pollutant with distance from a road.

Study and Location		% Fraction of Maximum (close to road)	% Above Background (steady-state)	Traffic Data at Nearby Road (vehicles/day)
Singer (LA) (9)	NO_2	0.55	0.5	200,000
Kodama (Tokyo) (10)	NO_2	0.78	0.15	60,000
Gilbert (Montreal) (11)	NO_2	0.75	0.3	100,000
Roorda-Knape (Netherlands) (12)	NO_2	0.6	0.1	100,000
Roorda-Knape (Netherlands)	Black Smoke	0.55	0.1	120,000
Zhu (high diesel) (LA) (8)	Black Smoke	0.3	0.3	200,000
Zhu (low diesel) (LA)	Black Smoke	0.3	0.5	200,000
Zhu (both) (LA)	$PM_{1.0}$	.15	n/a	200,000

Table 1: Fractions of Pollutant Concentrations (NO_2, Black Smoke, PM1.0) at 150 m from Major Roads

Study and Location	Distance from Busy Road (m)	Fraction of Max. $PM_{2.5}$ at this Distance	Traffic Data at Nearby Road (vehicles/day)
Nitta (Tokyo) (13)	150	0.8	>50,000
Roorda-Knape (Netherlands) (12)	300	0.90	>120,000
Janssen (Netherlands) (14)	1000	0.82	15,000
Hoek (Munich) (15)	>1000	0.84	"traffic site" compared to urban background
Hoek (Netherlands) (15)	>1000	0.79	"traffic site" compared to urban background

Table 2: $PM_{2.5}$ Pollutant Fractions (of Roadside Maximum) at Varying Distances from Traffic Sites

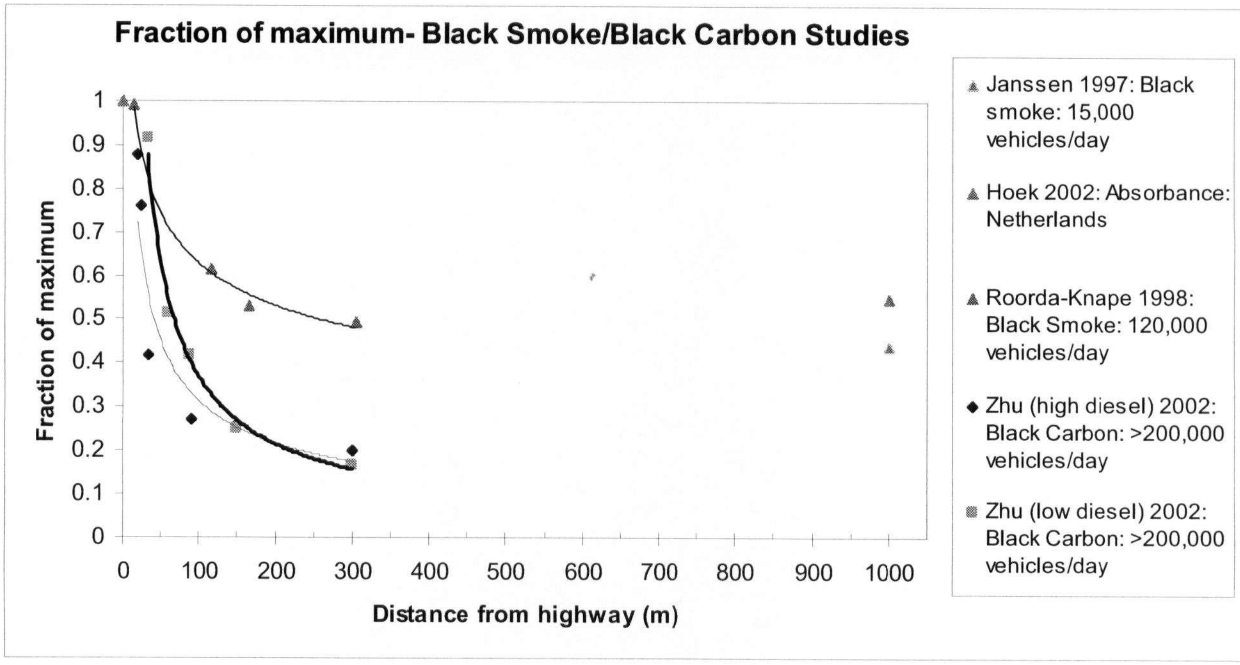

Figure 1: Black Smoke Concentration Reduction with Distance from Major Roads

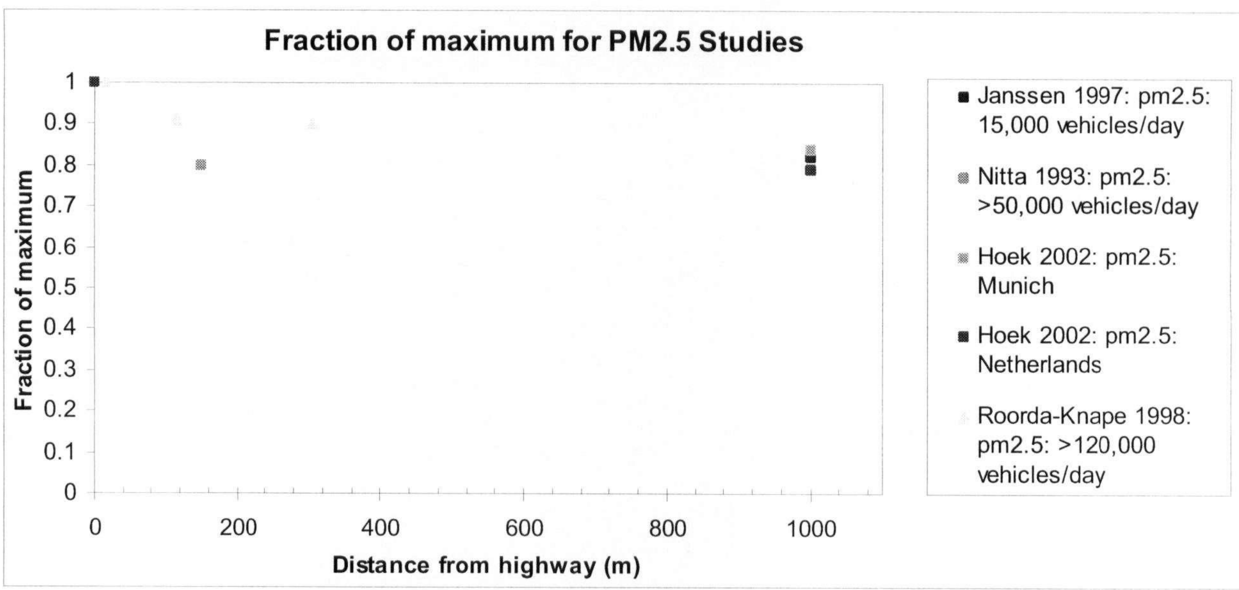

Figure 2: $PM_{2.5}$ Concentration with Distance from Major Roads

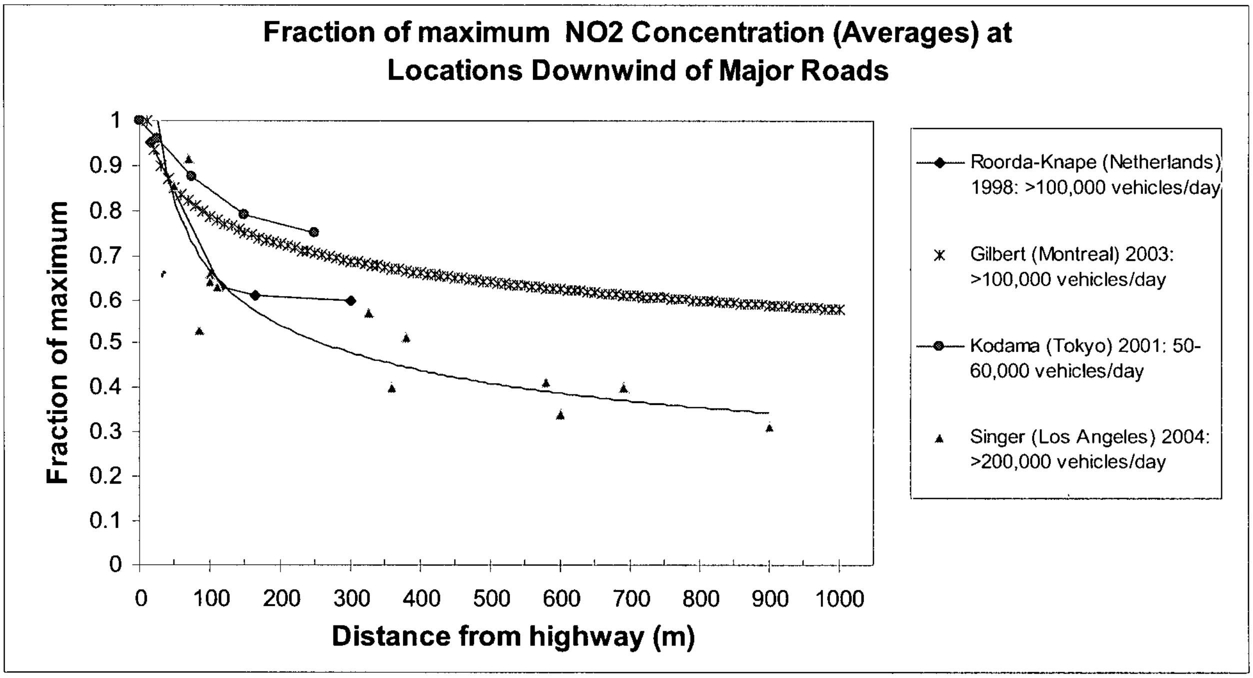

Figure 3: NO_2 Concentration Reduction with Distance from Major Roads

Traffic Volumes and Pollution Gradients

Vehicle traffic (annual daily traffic counts) on the major roads in these studies varied from over 15,000 vehicles per day to 200,000 vehicles per day. Reported gradients of traffic-based pollutants are similar for most roads with more than 15,000 vehicles per day when sampled downwind of the roadway. Road dust (primarily particles larger than $PM_{2.5}$) concentrations measured at roadside are higher than background but few studies have examined the impact of road dust on health. The California EPA land use handbook (6) suggests green space and regular watering to reduce suspended dust near schools but no specific evidence of effectiveness of such practices is available. Measurements upwind of major roads decrease only slightly, or not at all, with distance from road. Increased wind speeds cause pollutants to disperse more rapidly, and background concentrations are reached even closer to the roadway.

Higher traffic volumes generally increase pollutant concentrations at roadside, but the concentration gradient is comparable for both higher and lower traffic volumes. **For most traffic volumes and pollutants, the major decrease in traffic-based pollutants occurs in the first 150-200 metres from the roadside.** Pollutants decline at much slower rates from 150-1000 metres from the roadside. Statistical (regression) models for pollutant concentrations generally found logarithm of the distance from the roadway, wind speed and wind direction to be the greatest predictor of pollutant decline with distance from a major road.

Traffic Speed and Pollution

Similar concentration gradients are measured for both highways (8) and urban "high-traffic" roads (11) with relatively lower traffic speeds. In general, idling vehicles emit higher pollution concentrations than moving vehicles (7,16) . However, few studies to date have measured the differential health effects of idling-traffic pollution as compared to highway pollution. One study is available that compared moving and stop-and-go traffic. In this study conducted in Cincinnati area, infants exposed to stop-and-go bus and truck traffic had a significantly increased risk for wheezing without a cold compared with infants unexposed to truck or bus traffic or compared with infants exposed to moving truck traffic with a larger volume of trucks (17).

Topography and Street Canyons

In addition to windspeed and direction, urban topography can significantly alter the dispersion of traffic-based pollution from a major road. A specific type of urban topography is a street canyon: a canyon formed in a street between two rows of tall buildings.

A street canyon is defined by calculating the ratio of the height (H) of the buildings and the width (D) of the street. The following table is used to define a street canyon (18) :

H/D Ratio	Type of Roadway
<0.3	Wide street
0.3 to 0.7	Canyon street **without** risk of pollution accumulation
>0.7	Canyon street **with** risk of pollution accumulation

Table 3: Street Canyon Definitions

Street canyons can trap and limit dispersion of pollutants, due to the lack of wind flow out of the canyon. As a result, the concentration of pollutants in street canyons can be significantly elevated over urban-background levels (19). In many locations, including the British Columbia Lower Mainland, under typical meteorological conditions, traffic related air pollution concentrations are higher in low elevation areas.

Specific local and regional meteorological conditions that can lead to high air pollution episodes should be addressed with overall air quality management strategies and are not the focus of this document.

Road Type and Traffic Levels (B.C.)

Road classification data for British Columbia are available from the Digital Road Atlas (DRA) (http://bcdra.refractions.net/), as well as from commercial databases such as DMTI Spatial (http://www.dmtispatial.com/).

DMTI uses five classifications:

1. Expressway;
2. Highway Principal;
3. Highway Secondary;
4. Major; and
5. Local.

DRA uses:

1. Freeway;
2. Highway;
3. Arterial;
4. Collector; and
5. Local.

DRA further classifies roads with eight subclasses as shown in Table 4, below.

A measurement program in the Greater Vancouver Regional District linked elevated air pollution levels to locations up to 200 metres from DMTI classification types 1-4 (expressways, principal and secondary highways, and major roads). It also linked elevated pollution concentrations to locations up to 750 metres from a designated truck route (20). Although at present trucks represent a specific vehicular source of air pollution, expected reductions in (diesel) truck emissions (for example resulting from application of particle traps and the use of low-sulphur fuel) combined with turnover in truck fleets are expected to decrease total truck emissions in the long term. However, truck routes are expected to continue to be classified as "busy roads" even as (diesel) truck emissions are reduced and approach those of (spark-ignition engine) car emissions.

Levels of traffic on of different classifications have been compared (21) and show the general relationships described in Table 4, below. **The shaded rows are classifications/traffic levels that are considered significant sources in terms of air pollution.**

DMTI Class	*Count data (mean)*	DRA Class	*Count data (mean)*	DRA Subclass	*Count data (mean)*
Local	6,511	Local	3,976	Local	4,126
Major	15,207	Collector	8,953	Collector minor	8,580
				Collector major	9,964
Highway Secondary	18,254	Arterial	18,457	Arterial minor	15,321
				Arterial major	17,407
Highway Principal	21,025	Highway	27,961	Highway minor	22,242
				Highway major	36,684
Expressway	113,789	Freeway	113,789	Freeway	113,789

Table 4: Road Classifications Available for B.C. Roads and Mean Traffic Count Data from (21)

Levels of traffic for highways and selected major roads are available for B.C. from the Ministry of Transportation (http://www.th.gov.bc.ca/publications/planning/Trafficvolumes/index-trafficvolumes.htm); additional data for Greater Vancouver is available from (http://www.city.vancouver.bc.ca/engsvcs/transport/traffic/counts.htm). For other roads, traffic data are available from municipal sources, although typically measurements are made for much shorter averaging periods such as for peak morning (two hours) or evening traffic periods. There is, however, only a moderate relationship between these shorter-term measurements and the longer-term averages that are most relevant for health assessment. For a select number of locations in the Lower Mainland, total daily traffic counts were found to be roughly 11 times higher than peak morning (7:30-8:30 am) hourly traffic counts (22). Truck routes are usually identified at the municipal level. In a community without existing truck routes, it may be appropriate to designate routes. Clearly, new truck routes should be sited to avoid the sensitive land uses identified in this document.

Health Impacts of Traffic-Related Air Pollution

Motor vehicle exhaust has long been known as a significant contributor to urban air pollution and its associated health effects. However, only recently have studies demonstrated that people living in areas near major roadways experience increased health effects due to air pollution. Recently, the World Health Organization published a systematic review of the literature on transport-related air pollution that includes an in-depth evaluation of the associated health hazards (7). Overall, the report concludes that transport-related air pollution is associated with an increased risk of cardiovascular deaths and increased nonallergic respiratory disease. The report also states that transport-related pollution may be related to the onset of heart attacks, along with lung cancer, low birth weight and preterm births – although the evidence base is not limited to studies of roadway proximity.

Though only a few relevant studies have been conducted, residence within 100 metres of a freeway or major road is associated with increased deaths. Most studies have focused on childhood respiratory disease. They have linked living near major urban roads or freeways with increased respiratory symptoms (bronchitis, wheeze, chronic cough) and decreased lung function. There is also some evidence suggesting increased risk for asthma development. A growing number of studies have linked living near major roads or freeways during pregnancy to premature births or low-birth-weight babies.

Health effects studies differ in their approach to determining the impact of traffic-related air pollution, but they have relied mainly on simple measures of proximity, measurements or models. In terms of proximity, most studies use distances of 50-300 metres to indicate exposure to traffic-related air pollution. In studies in Holland (23;24), an association between decreased lung function in children and exposure to truck traffic was strongest for children living within 300 metres of motorways. In addition, chronic respiratory conditions (cough, wheeze, runny nose, and doctor-diagnosed asthma) were reported more often for children living within 100 metres from the freeway.

The specific health effects linked to roadway proximity are summarized in this table:

Health Outcome	**Evidence**
Mortality	Strong
Respiratory diseases (nonallergenic)	Strong
Respiratory diseases (allergic)	Unclear (Studies indicate both positive and negative associations.)
Reproductive outcomes	Moderate (Some inconsistencies in studies)
Cardiovascular diseases	Moderate (Relatively few studies)
Cancer	Unclear (Limited evidence)

Table 5: Summary of Health Studies of Air Pollution and Roadway Proximity

As discussed, studies suggest that traffic proximity is linked with adverse pregnancy outcomes, childhood respiratory disease and cardiovascular mortality. The populations at increased risk for health impacts of traffic-related air pollution include pregnant women, children and older adults – especially those with pre-existing cardiac disease.

At present it is premature to quantify the expected impact that application of this BMP would have on health within British Columbia, based on European data, the roadway proximity effect is responsible for as much as a doubling of mortality risks (7,25). Therefore, completely removing sensitive individuals from the impact of traffic-related air pollution could reduce air pollution related mortality by up to 50%.

Glossary

Black Smoke

A measure of the blackness of airborne particulate matter. This is determined by passing the air through standard filter paper and measuring the blackness of the stain that is produced. Blackness is related to the amount of elemental carbon and is an indicator of vehicle-related particulate matter.

Downwind

The direction toward which the wind is blowing. With the wind.

Elemental Carbon

Inorganic carbon, as opposed to carbon in organic compounds, sometimes used as a surrogate measure for diesel particulate matter, especially in occupational health environments.

Freeway (or other busy traffic corridor)

Roadways that, on an average day, have traffic in excess of 50,000 vehicles in a rural area or 100,000 vehicles in an urban area.

Gradient

The rate at which a physical quantity, such as temperature or pressure, increases or decreases relative to change in a given variable, especially distance (in a specified direction).

High-Efficiency Particulate Air (HEPA) Filter

Efficient mechanical filters that remove 99.97% of particles of an aerodynamic diameter of 0.3 micrometres – the most penetrating particle size. Generally, efficiencies are higher for larger and smaller particles . These filters can be portable room filters, or centralized building units.

Highway

A major road within a city, or linking several cities together.

Idling

Running a vehicle while it is sitting still for more than about 10 seconds. Idling can release a substantial amount of pollutants.

Log (Logarithm)

An exponent used in mathematical equations to express the level of a variable quantity.

Metrics

Specific indicators that are measured in order to assess a pollutant's impact on the physical or social environment.

Particle Number Concentration

The number of particles per volume of air.

Particle Number Distributions

The numbers of **differently sized** particles in the air.

Particulate Matter (PM)

Small gas and liquid particles in the atmosphere:

- PM_{10}: particulate matter that is 10 micrometres in (aerodynamic) diameter
- $PM_{2.5}$: particulate matter 2.5 micrometres and less in (aerodynamic) diameter
- $PM_{1.0}$: very small particulate matter, 1.0 micrometres and less in (aerodynamic) diameter.

Road, Busy

Busy road is defined as a road with greater than 15,000 vehicles/day, based on annual daily average traffic counts.

Roadway

Road over which vehicles travel (same as "road").

Street Canyon

A canyon formed in a street between two rows of tall buildings. Vehicle exhaust fumes (in particular) are trapped there because the buildings on each side protect the street from the wind. If wind directions do not flow parallel to the street, pollutants can build up to high concentrations.

Turbulence

An instability in the atmosphere that disrupts the wind flow, causing gusty, unpredictable air currents.

Ultrafine Particles

Very small atmospheric particles, 0.1 micrometres and less in diameter.

Upwind

The direction from which the wind is blowing. Against the wind.

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