Modeling Residential Fine Particulate Matter Infiltration: Implications for Exposure Assessment

by

Perry Wesley Hystad
B.Sc., University of Victoria, 2004

A thesis submitted in partial fulfillment of the
requirements for a degree of

MASTERS OF SCIENCE

in the Department of Geography

SUPERVISORY COMMITTEE

for

Modeling Residential Fine Particulate Matter Infiltration:
Implications for Exposure Assessment

Dr. Peter Keller, supervisor
(Dean of Social Sciences, Department of Geography)

Dr. Les Foster, committee member
(Department of Geography, and School of Child and Youth Care)

Dr. Denise Cloutier-Fisher, committee member
(Department of Geography, and Centre on Aging)

SUPERVISORY COMMITTEE

Dr. Peter Keller, supervisor
(Dean of Social Sciences, Department of Geography)

Dr. Les Foster, committee member
(Department of Geography, and School of Child and Youth Care)

Dr. Denise Cloutier-Fisher, committee member
(Department of Geography, and Centre on Aging)

ABSTRACT

This research investigates the difference between indoor and outdoor residential fine particulate matter ($PM_{2.5}$) and explores the feasibility of predicting residential $PM_{2.5}$ infiltration for use in exposure assessments. Data were compiled from a previous study conducted in Seattle, Washington, USA and a new monitoring campaign was conducted in Victoria, British Columbia, Canada. Infiltration factors were then calculated from the indoor and outdoor monitoring data using a recursive mass balance model. A geographic information system (GIS) was created to collect data that could be used to predict residential $PM_{2.5}$ infiltration. Spatial property assessment data (SPAD) were collected and formatted for both study areas, which provided detailed information on housing characteristics. Regression models were created based on SPAD and different meteorological and temporal variables. Results indicate that indoor $PM_{2.5}$ is poorly correlated to outdoor $PM_{2.5}$ due to indoor sources and significant variations in residential infiltration. A model based on a heating and non-heating season, and information on specific housing characteristics from SPAD was able to predict a large portion of the variation within residential infiltration. Such models hold promise for improving exposure assessment for ambient $PM_{2.5}$.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF APPENDICES

ACRONYMS

a:	Air exchange coefficient
a_1:	Constant in linear regression equation
a_2:	Constant in linear regression equation
CRD:	Capital Regional District
ETS:	Environmental Tobacco Smoke
FEV:	Forced expiratory volume
F_{inf}:	Infiltration factor
GBPS:	Georgia Basin Puget Sound airshed
HVAC:	Heating, ventilation and air conditioning systems
INTAIR:	Interior air quality model
I/O $PM_{2.5}$:	Indoor and outdoor difference in fine particulate matter
k:	Deposition coefficient
MENTOR:	Modeling environment for total risk
NH_3:	Ammonia
Neph:	Nephelometer
No_x:	Nitrogen Oxides
O_3:	Ozone
PEF:	Peak expiratory flow
PTEAM:	Particle team study conducted by Harvard University
p:	Penetration coefficient
$PM_{2.5}$:	Fine particulate matter
PM_{10}:	Coarse particulate matter
PM:	Particulate matter
RISK:	Indoor air quality model
SHEDS:	Stochastic Human Exposure and Dose Simulation
SPAD:	Spatial Property Assessment Data
SO_x:	Sulfur Oxides
UBC:	University of British Columbia
UVIC:	University of Victoria
UoW:	University of Washington

ACKNOWLEDGEMENTS

This research would not have been possible without the support of a great number of people. Firstly, I must thank my supervisor Dr. Peter Keller for his advice and support, not only throughout this research, but during all my years at UVic. My committee members, Dr. Leslie Foster and Dr. Denise Cloutier-Fisher, also must be thanked for their time and effort in providing insightful comments and ideas for my thesis. Eleanor Setton supplied immeasurable guidance, and without her in the lab corner I am sure I would still be grinding away. The entire BAQS team provided valuable assistance and advice, particularly Dr. Michael Brauer and Dr. Tim Larson. Dr. Ryan Allen also was a significant source of information for the Seattle data and the infiltration calculations. I am sure I am forgetting a number of people, but you know who you are and I am very grateful for everyone's help and support during these last two years!

1 Introduction

This research investigates the differences between indoor and outdoor residential fine particulate matter ($PM_{2.5}$) and explores the feasibility of predicting residential $PM_{2.5}$ infiltration (defined as the amount of ambient $PM_{2.5}$ penetrating indoor and remaining suspended (Wilson et al. 2000)). The difference between indoor and outdoor ambient $PM_{2.5}$ hereafter will be referred to as I/O $PM_{2.5}$. An index to other abbreviations and acronyms used throughout the thesis can be found on Page xii.

Recent research in population health, epidemiology, and health geography have demonstrated the impacts of air pollution on human health (Boman et al. 2003; Burnett et al. 1998; Hirsch et al. 1999; Raaschou-Nielsen et al. 2001). As far back as the London Fog of 1952, negative associations between air pollution and human health have been widely recognized; however, the impacts of air pollution on our daily lives continue to persist. The 2002 World Health Organization's Global Burden of Disease Initiative estimated that ambient (outdoor) air pollution causes approximately 800,000 premature deaths per year (Ezzati et al. 2002).

Fine particulate matter is a major component of air pollution causing health impacts. Large cohort studies (Abbey et al. 1993; Dockery et al. 1993; Pope 2000; Schwartz et al. 1996) have shown several increased health risks associated with increased levels of $PM_{2.5}$, such as cancers, decreased lung function, premature mortality, chronic respiratory and cardiovascular diseases, and associated increases in hospital and emergency room visits. No indication of a threshold value for health impacts currently exists for $PM_{2.5}$ (Kappos et al. 2004).

Health impacts of $PM_{2.5}$ are primarily examined through epidemiological studies that use proxies for assessing the amounts of $PM_{2.5}$ an individual is exposed to. The majority of epidemiological studies use $PM_{2.5}$ data from ambient fixed site monitoring networks at residential locations to represent personal exposure. This has many inherent limitations that may mask the true relationship between $PM_{2.5}$ and health effects (Hanninen et al. 2005a; Ozkaynak et al. 1999; Wallace et al. 2003).

The main limitation of using outdoor $PM_{2.5}$ as a surrogate for personal exposure is the assumption that outdoor $PM_{2.5}$ is equal to indoor $PM_{2.5}$. The majority of personal exposure occurs inside the home residence due to the long periods of time people spend indoors at home (Burke et al. 2001; Leech et al. 2004). Numerous studies have shown that the highest exposure correlations between outdoor, indoor and personal monitoring are those between personal exposure measurements and indoor residential pollution concentrations. Personal exposure correlations to outdoor measurements were considerably lower (Kousa et al. 2001; Meng et al. 2005; Rea et al. 2001).

Infiltration of $PM_{2.5}$ into residential environments constitutes the primary mechanism that determines differences between I/O $PM_{2.5}$. Different $PM_{2.5}$ infiltration factors may introduce significant error into exposure assessments due to the long periods of time individuals spend inside their homes (Hanninen et al. 2005a; Meng et al. 2005). The US National Research Council (2001) suggested that one of the remaining uncertainties associated with $PM_{2.5}$ exposure research is the estimation of ambient origin $PM_{2.5}$ contributions to residential indoor and personal exposure. To date, no methodology has been developed to predict indoor ambient $PM_{2.5}$ for individual residences in a large study population.

1.1 Research Questions

The aim of this research is twofold. First, I/O $PM_{2.5}$ in non-smoking homes within the Capital Regional District (CRD) of Victoria, British Columbia (BC) Canada are measured to examine the differences between residential I/O $PM_{2.5}$ and the resulting implications for exposure assessment. Second, the feasibility of creating an infiltration model, based on residential monitoring samples from both the CRD and Seattle Washington, USA are explored. Spatial Property Assessment Data (SPAD) are a data source that contains substantial information on building characteristics known to influence $PM_{2.5}$ infiltration (for example, year built, square footage, building type, building value, or heating source) and is available for every residence in the Georgia Basin Puget Sound (GBPS) airshed, which includes the CRD and Seattle. It is hypothesized that an infiltration model incorporating housing characteristics from SPAD and meteorological variables could predict a significant component of indoor ambient $PM_{2.5}$ and would therefore improve current ambient $PM_{2.5}$ exposure predictions used in epidemiology research.

This research will address the following three major research questions:

1.) What are the differences between I/O $PM_{2.5}$ levels in the CRD and what impacts do these differences have on exposure assessment?

2.) What are the relationships between $PM_{2.5}$ infiltration, building attributes from SPAD, seasonality and meteorological variables?

3.) Can a combination of building attributes and meteorology be used to predict ambient $PM_{2.5}$ inside individual residences in the GBPS airshed?

2 Literature Review

2.1 Fine Particulate Matter Air Pollution

Fine particulate matter consists of all suspended airborne particles under 2.5 microns, which includes many different substances that originate from different sources and precursor gases (Keeler et al. 2005). The major components of $PM_{2.5}$ include sulphates, carbonaceous materials, nitrates, trace elements, and water. Fine particulate matter can be characterized by origin (e.g. anthropogenic or geogenic, primary or secondary particles), by source (e.g. combustion originated), or by physical chemical properties (e.g. solubility); however, for practical reasons particles are typically classified by size (e.g. Ultra fine (UF), $PM_{2.5}$, PM_{10}, or Total Suspended Particles (TSP)) (Englert 2004). Figure 1 illustrates different particle size contributions relative to ambient concentrations.

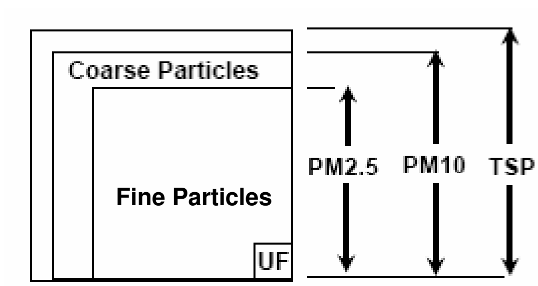

Figure 1. Particle size relative to ambient PM concentrations (Englert 2004).

Fine particulate matter is both a primary and a secondary pollutant. Secondary $PM_{2.5}$ forms from gas-to-particle conversion processes (e.g. coagulation and condensation). Predominant precursor gases include Sulfur Oxides (SO_x), Nitrogen Oxides (NO_x), Volatile Organic Compounds (VOCs), and Ammonia (NH_3). Outdoor generated $PM_{2.5}$ (ambient $PM_{2.5}$) arise from natural or anthropogenic sources (White and

Suh 2003). The main natural sources of ambient $PM_{2.5}$ are forest fires, sea spray, windblown soil, and pollen. Anthropogenic $PM_{2.5}$ sources primarily include motor vehicles and transportation, manufacturing and production, and space heating.

Indoor sources of $PM_{2.5}$ are attributed to behavioural factors and have traditionally received less attention in epidemiology research than their outdoor counterparts, primarily due to the difficulty predicting indoor $PM_{2.5}$ concentrations. Table 1 illustrates the potential sources of indoor particulates (Owen et al. 1992).

Table 1. Sources of indoor particulates.

Source Type	**Description**
Plant	pollens, spores, molds, miscellaneous byproducts (finely ground grains, coffee, cornstarch)
Animal	bacteria, viruses, hair, insect parts and byproducts, epithelial cells (e.g. dandruff)
Mineral	asbestos, talc, man-made mineral fibres, elemental particles (carbon)
Combustion	tobacco smoke, cooking, heating appliances
Home/personal care products	sprays, humidifiers
Radioactive	radon progeny

Undeniably, the largest source of indoor $PM_{2.5}$ is environmental tobacco smoke (ETS) (Dockery and Spengler 1981b; Lebret et al. 1987; Letz et al. 1984). Dockery and Spengler (1981a) estimated that smoking one pack of cigarettes a day inside a home raised 24 hour indoor particle levels by approximately 18 $\mu g/m^3$, and in air-conditioned buildings, where infiltration factors were minimal, smoking contributed an additional 42 $\mu g/m^3$ of particles.

In the absence of ETS, intensive cooking has been associated with higher concentrations of $PM_{2.5}$, as well as cleaning, vacuuming, dusting, heating, and general activity with the home (Abt et al. 2000; Thatcher et al. 2003; Jones 1999). There is a shortcoming in the literature to how much these sources contribute to indoor residential exposure, how high $PM_{2.5}$ concentrations are elevated during indoor source activities, and how long indoor generated $PM_{2.5}$ levels are elevated (Thatcher et al. 2003). A study by Koutrakis et al. (1992) could not identify approximately 25% of all indoor sources contributing to $PM_{2.5}$ levels. This may be due to the nature and age of building materials and cleaning products (e.g. paints, waxes, and adhesives) or to the fact that a substantial portion of indoor $PM_{2.5}$ originates from sources that have not, or cannot, be accurately identified (Koutrakis et al. 1992).

The lack of knowledge surrounding indoor sources of $PM_{2.5}$, specifically those other than ETS, and their contributions to indoor residential exposure, is due to the fact that new technologies have only recently become available that allow researchers to measure $PM_{2.5}$ on an accurate and continuous basis. The lack of information on the spatial and temporal variations in $PM_{2.5}$ concentrations indoors and the differences between I/O $PM_{2.5}$ are avenues of research that need to be further addressed.

2.2 Health Effects of $PM_{2.5}$

Health effects of $PM_{2.5}$ are typically examined through epidemiological studies that attempt to find statistical associations between pollution levels, usually ambient outdoor concentrations, and health outcomes. Epidemiological studies, in spite of limitations connected to current exposure mechanisms, provide a basis for exposure-response functions and play an important role in setting health and regulatory standards (Aunan 1996). The following is a brief review of the epidemiological literature, both acute (short-term effects) and chronic (long-term effects), on $PM_{2.5}$ and health effects.

The acute impacts of $PM_{2.5}$ have been linked to a number of health effects. Increases in death counts and the numbers of people admitted to hospital for cardiovascular or respiratory diseases have been linked to short term increases in ambient $PM_{2.5}$ (Atkinson et al. 1999; Lipfert et al. 2000; Schwartz et al. 1996). Samet et al. (2000) assessed the effects of five major air pollutants (PM, O_3, CO_2, SO_2, and NO_2) on daily mortality rates in twenty of the largest cities in the United States from 1987 to 1994. They found that the estimated increase in the relative rate of death from cardiovascular and respiratory causes was 0.68 percent for each increase in the PM (includes $PM_{2.5}$ as well as larger particle sizes) level of 10ug/m^3. Figure 2 summarizes the acute health effects of $PM_{2.5}$ (Pope 2000) (FEV=forced expiratory flow, PEF=peak expiratory flow).

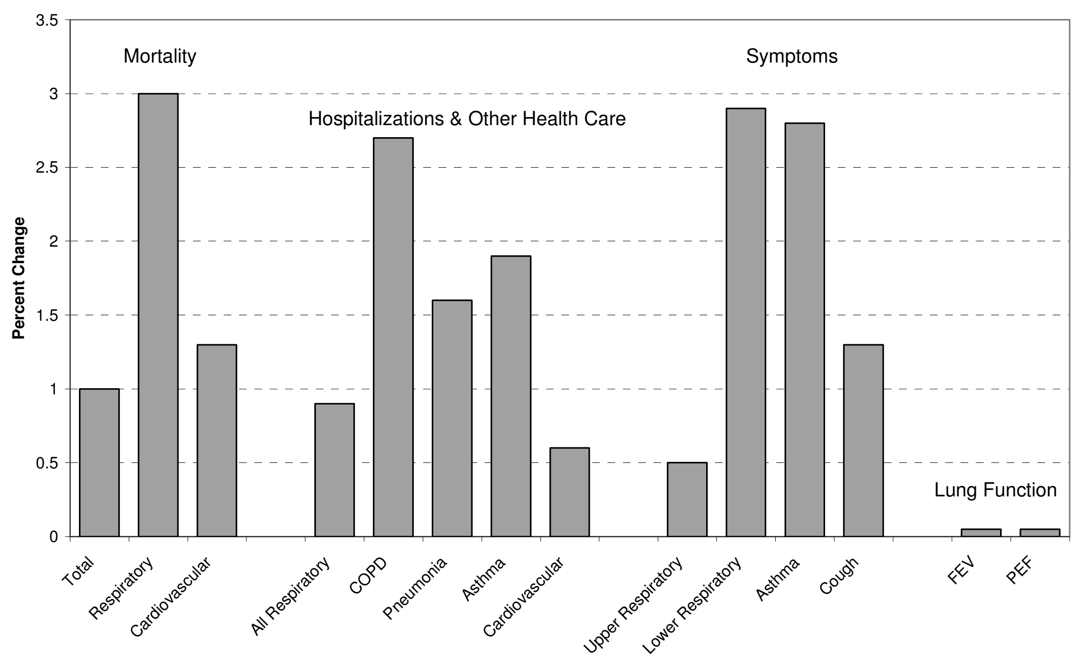

Figure 2. Summary of acute health effects presented as approximate percent changes in health end points per 5ug/m3 increase in $PM_{2.5}$ (Pope 2000).

Levels of the other pollutants were not significantly related to mortality rates. Significant evidence also links acute $PM_{2.5}$ events with a number of detrimental influences to individuals with asthma or other respiratory problems (McConnell et al. 1999; Peters et al. 1997; Wichmann and Peters 2000). Patients with cardiovascular complications and diabetes also are affected by high levels of acute $PM_{2.5}$ leves (Zeka et al. 2005).

Studies examining the chronic effects of $PM_{2.5}$ have also found links between long term $PM_{2.5}$ exposure and health effects. Initial research of chronic $PM_{2.5}$ impacts compared polluted cities to clean cities and their associated life expectancy rates (Laden et al. 2000; Samet et al. 2000) or focused on chronic mortality (Abbey et al. 1999; Hoek et al. 2002; Pope 2000). These studies indicated that polluted cities had higher extra deaths than expected and higher loss of life expectancy by population than cleaner cities, and increases in $PM_{2.5}$ were positively associated with increased mortality rates. More specific health outcomes such as pulmonary function, cardiovascular morbidity, respiratory illness, and cancer have been examined but findings are inconsistent. Figure 3 illustrates the documented health effects of chronic $PM_{2.5}$ (Pope 2000) (FVC=forced vital capacity, PEV=peak expiratory volume).

Inconclusive results may emerge from epidemiological studies, both chronic and acute, due to exposure misclassification. For example, it has been shown that the time frame of exposure for infants is short (a few months rather than years) and that this exposure occurs primarily in the home (Pope 2000). Exposure mechanisms have not been developed that can predict short-term exposures for specific environments, such as the home, for large populations. Since infants are likely at greater risk to the health effects of $PM_{2.5}$, it is essential to create exposure mechanisms that predict exposure where children, and the general population, spend the majority of their time (indoors at home), as the use of central-site air quality monitoring stations to estimate the effects on individuals who spend most of their time indoor remains uncertain (Pope 2000).

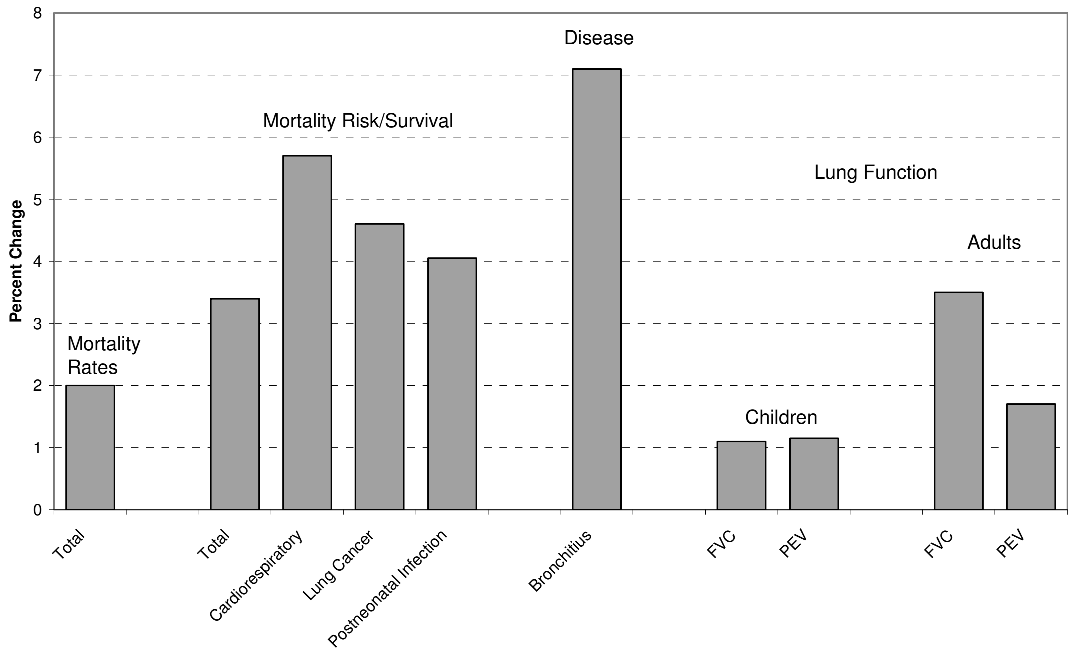

Figure 3. Summary of chronic health effects presented as approximate percent changes in health end points per 5ug/m3 increase in $PM_{2.5}$ (Pope 2000).

2.3 Predicting Personal Exposure to $PM_{2.5}$

The majority of $PM_{2.5}$ exposure assessments in large epidemiology studies use outdoor ambient $PM_{2.5}$ to represent personal exposure, even though people generally spend less than ten percent of each day outdoors and approximately 70% of their day inside their home, as shown in Figure 4 (Klepeis et al. 2001). A logical step to improving existing ambient exposure assessments is to predict exposure for indoor residential $PM_{2.5}$.

Currently, large epidemiology studies use a number of methods to predict personal exposure to $PM_{2.5}$. These methods are becoming increasingly spatially refined and have moved from interpolating fixed site monitoring data, where very few sites may be used to represent an entire study population, to land use regression and dispersion modelling techniques that are able to predict $PM_{2.5}$ at local or neighbourhood levels. The problem with these techniques however is that they still predict outdoor ambient $PM_{2.5}$ only, and therefore make the assumption that outdoor $PM_{2.5}$ is representative of indoor $PM_{2.5}$ or that infiltration is the same for all residences.

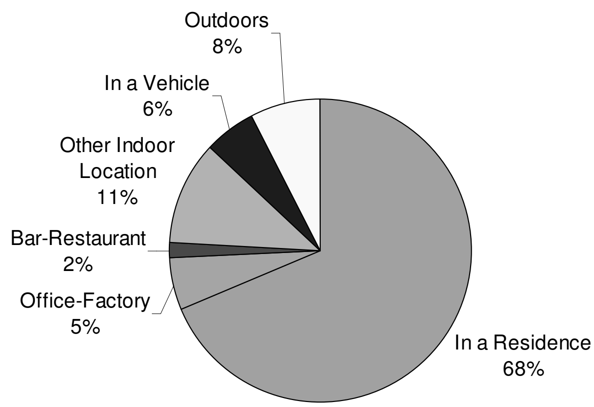

Figure 4. Time spent by individuals in different environments (Klepeis et al. 2001).

2.4 Indoor $PM_{2.5}$ Exposure Methods

Exposure models that predict indoor $PM_{2.5}$ are limited primarily by the lack of widely available data for individual residences. Predicting indoor $PM_{2.5}$ exposure requires models that incorporate the influence of buildings and indoor activities, data that traditionally have not been widely available. A number of different types of models predict either indoor $PM_{2.5}$ for small numbers of individual buildings, requiring data intensive observations that cannot be collected for large numbers of residences, or that use stochastic (probabilistic) modeling techniques to predict average indoor $PM_{2.5}$ for large populations. No indoor exposure models currently exist that predict indoor $PM_{2.5}$ for individual residences at a large scale.

Mathematical models do exist that use data intensive equations to predict the relationship between indoor particle concentrations and outdoor levels. The physical model Interior Air (INTAIR) is an example of a dynamic compartment model that estimates indoor concentrations of $PM_{2.5}$ by solving differential equations (Dimitroulopoulou et al. 2001). Similarly, the latest US environmental protection agency (EPA) indoor air quality model 'RISK' is designed to allow calculations of individual exposure to indoor air pollutants from different sources. The model uses data on source emissions, room-to-room air flows, air exchange, and indoor sinks to predict pollutant concentrations. The model also considers a wide range of sources including long term sources, on/off indoor sources, and decaying sources. The obvious problem with this model, similar to other mathematical indoor pollution models, is that the required data are not available for individual residences, which restricts the model to a limited number of residences where these data have been measured or requires input distributions and stochastic modeling approaches.

Existing population models (MENTOR/SHEDS/Models-3) use stochastic modeling approaches and are therefore limited to determining indoor $PM_{2.5}$ concentrations through the use of similar modelling parameters, including infiltration coefficients and indoor source activities, for all residences (Georgopoulos et al. 2005). The output exposures for these types of models are limited to predicting exposure distributions for broad categories of indoor environments, such as classrooms, residences, or offices, and do not account for individual home variability. For example, infiltration of ambient $PM_{2.5}$ into residences may be estimated as 0.6, which assumes that indoor concentrations of ambient $PM_{2.5}$ are 60% of the outdoor ambient concentrations. The large variation found between residential infiltration factors (for example, 0.1 to1.0) contradicts the use of one infiltration factor for all residences, even in a small geographic region, since one infiltration factor will incorporate significant exposure misclassification into residential exposure estimates (Allen et al. 2003; Meng et al. 2005; Wallace and Williams 2005). The ability to apply an infiltration model to estimate the amount of ambient $PM_{2.5}$ that infiltrates inside individual residences would substantially improve exposure assessments.

The complexity of existing indoor $PM_{2.5}$ models and the limitations associated with these models have led to the widespread use of I/O $PM_{2.5}$ ratios to predict indoor total and ambient $PM_{2.5}$ (Dockery and Spengler 1981a; Monn et al. 1997; Monn 2001; Wallace 1996). Three of the largest studies, the Harvard Six-city study (Spengler et al. 1981) the New York State ERDA study (Sheldon et al. 1989) and the EPA PTEAM study (Ozkaynak et al. 1996) all found low levels of consistency between I/O $PM_{2.5}$ ratios, suggesting that more research is needed to further characterize the relationships between I/O $PM_{2.5}$. Figure 5 and Figure 6 summarize the distribution of published I/O $PM_{2.5}$ ratios under both indoor non-source and source conditions. The large variability of I/O ratios illustrates the importance of the indoor environment as a modifier of personal exposure. For example, the use of an I/O ratio of 0.57 versus 1.06 will nearly half indoor $PM_{2.5}$ exposure estimates and therefore result in significantly changed personal exposure estimates.

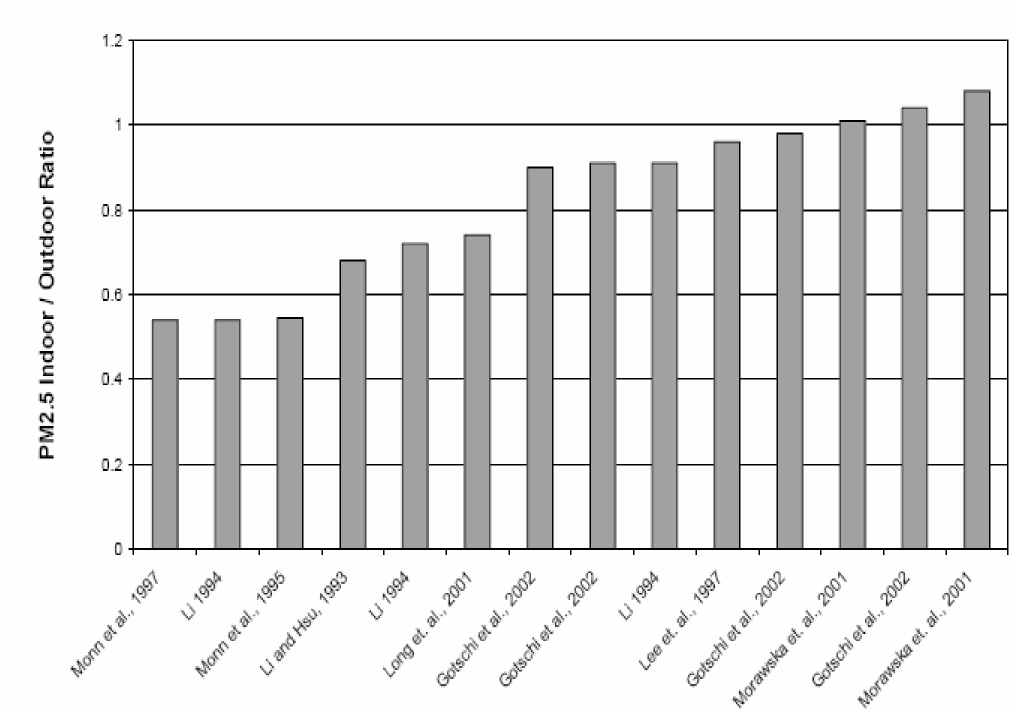

Figure 5. Summary of published data on I/O $PM_{2.5}$ ratios in the absence of known indoor particle sources.

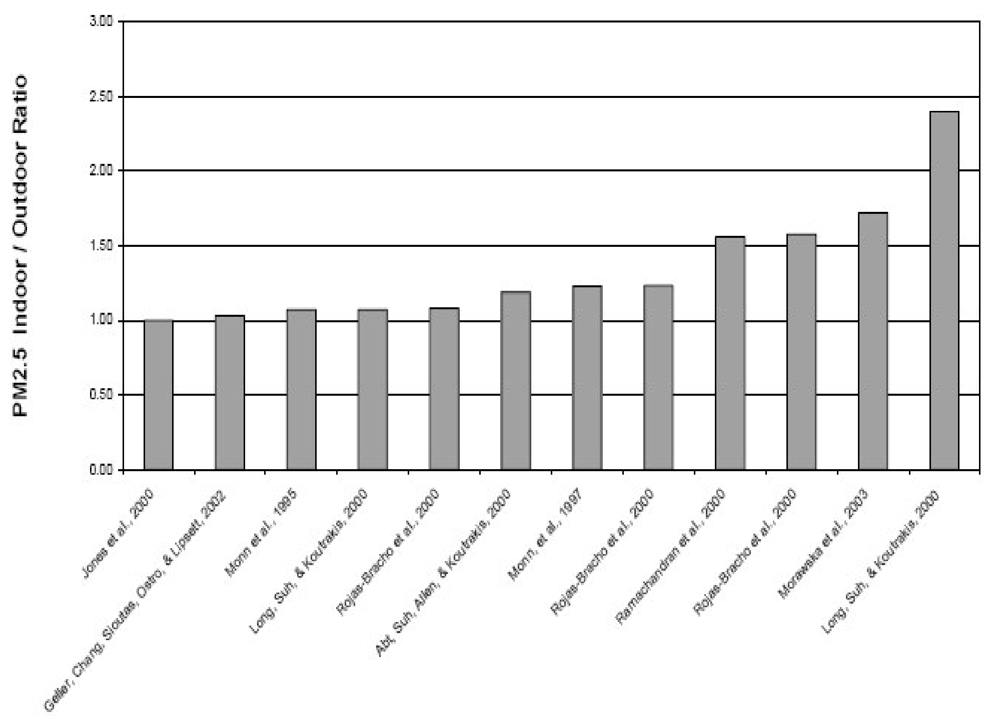

Figure 6. Summary of published data of I/O $PM_{2.5}$ ratios under indoor particle source conditions.

The variation found between residential I/O $PM_{2.5}$ may be due to a number of factors. Studies are needed to examine residential I/O $PM_{2.5}$ within distinct climate regions, as different building characteristics and residential heating and cooling systems change between regions and may therefore affect I/O $PM_{2.5}$ (Hanninen et al. 2005b). This study provides I/O $PM_{2.5}$ measurements for a large residential sample in the Pacific Northwest (representing mild upper-mid latitude coastal conditions) in a housing sample with few air conditioning units (i.e. less than three percent) (BC Stats, 2002), a region with relatively low ambient $PM_{2.5}$ levels, and a region that has significant residential wood-heating emissions. Further understanding of population based I/O $PM_{2.5}$ ratios is important to improve population exposure models, I/O $PM_{2.5}$ risk assessments, and policy creation (Hanninen et al. 2004; Kruize et al. 2003).

Currently, indoor air quality exposure methods are useful for policy makers, risk assessments or ecological health analysis. To incorporate indoor exposure methods into epidemiological research, indoor exposures methods must begin to incorporate unique residential characteristics, which lead to the I/O $PM_{2.5}$ differences documented in previous studies (Allen et al. 2003; Hanninen et al. 2005b; Meng et al. 2005; Sheldon et al. 1989; Wallace and Williams 2005). Unfortunately, inputs into existing mathematical indoor air quality models do not exist at the population level. Direct measurements of indoor $PM_{2.5}$ would be the obvious method for improving indoor exposure estimates, but with large populations is not feasible.

Additional research is needed to further refine exposure assessment techniques that can account for the variability within residential indoor $PM_{2.5}$. The variability in residential infiltration is a large determinant of indoor exposure since indoor $PM_{2.5}$ levels are determined largely from ambient $PM_{2.5}$ levels (Janssen et al. 2001; Kousa et al. 2002; Williams and Ogston 2002). Infiltration factors are therefore critical exposure factors that may modify the health effect estimates reported in $PM_{2.5}$ epidemiological studies (Long and Sarnat 2004).

2.5 Calculating Residential $PM_{2.5}$ Infiltration

Infiltration can be defined as the equilibrium fraction of outdoor ambient $PM_{2.5}$ that penetrates inside a residence and remains suspended (Wallace 1996). Calculating residential infiltration efficiencies is an improvement on I/O $PM_{2.5}$ ratios because infiltration can be determined for residences under all occupant conditions, while I/O ratios either represent all pollutant sources or ambient I/O ratios, which are determined during non-source periods. Infiltration efficiencies therefore better capture the true relationship between I/O $PM_{2.5}$ and allow for the apportionment of indoor $PM_{2.5}$ into its indoor generated and ambient components. Figure 7 depicts the formation and removal processes that determine the infiltration factor of a residential building.

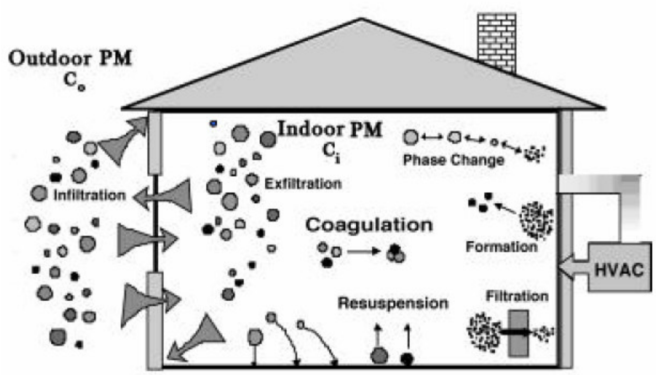

Figure 7. Indoor formation and removal processes of $PM_{2.5}$ in the absence of indoor sources (Sherman and Dickerhoff 1998).

Estimations of infiltration efficiency can be calculated using a variety of approaches, including outdoor tracer methods, recursive mass balance models (using continuous measurements), mass balance models (measurements of I/O concentrations and air exchange rates), or from I/O ratios during indoor non-source periods (Allen et al. 2003). The recursive model in combination with continuous measurements will be used in this research to determine residential infiltration factors.

2.5.1 The Recursive Mass Balance Model

The recursive mass balance model is an application of the mass balance equation (Nazaroff and Cass 1989) that calculates infiltration as a function of air exchange, deposition and penetration. This research uses a new approach developed by Allen et al. (2003) that applies continuous I/O $PM_{2.5}$ measurements to the mass balance equation (EQ1). The linear regression approach used to determine infiltration factors (F_{inf}) will be described in the data analysis chapter.

EQ1: $$F_{\text{inf}} = \frac{Pa}{a + k}$$

The variables of the mass balance equation (*P* penetration, *a* air exchange and *k* deposition) are examined in more detail to understand how they contribute to residential infiltration efficiency and in turn how housing characteristics, meteorology and indoor behaviours may affect infiltration.

Penetration (*P*) of ambient $PM_{2.5}$ indoors is influenced by several factors, including the physical and chemical characteristics of particles, meteorology, housing characteristics and the mechanisms of home air exchange. Currently, the efficiency of particle penetration through building shells is not adequately understood. The results of the PTEAM study (Özkaynak et al. 1996) showed penetration factors calculated using a nonlinear statistical approach very close to unity (1.00). Other studies have reported penetration factors of approximately 0.6-0.7 (Colome et al. 1992; Dockery and Spengler 1981a; Koutrakis et al. 1992; Lioy et al. 1990; Yocom, 1982). Further work is needed to more accurately determine penetration factors for different building characteristics, timeframes, and environmental conditions.

Air exchange rates depend on building characteristics as well as ambient conditions and resident activities (Allen et al. 2003). Outdoor air enters a building through doors, windows, cracks, and heating and ventilating systems. Air-conditioned and energy efficient homes tend to have very low air exchange rates, while older homes that have not been upgraded, for example, with new double paned windows, are more "leaky". Air exchange can range from a minimum 0.1 air changes per hour up to 10 changes per hour when doors and windows are fully open (US EPA 1995). Ambient conditions, particularly wind velocity and the difference between indoor and outdoor temperatures, create pressure differences during closed window scenarios that lead to higher air exchange rates.

Typically, the most important factor affecting air exchange rates is window opening behaviours. General climatic conditions (temperature, precipitation, wind speed, relative humidity) play an important role in determining window opening behaviours in a residence. This has been identified by studies able to predict window openings in homes based on meteorological conditions, specifically temperature and precipitation (Allen et al. 2003, Meng et al. 2005).

Once indoors, the deposition of ambient particles occurs through gravitational settling or electrostatic forces. Deposition rates depend on the size, shape, and density of particles, as well as airflow dynamics and deposition surface area (Wallace 1996). Larger particles tend settle to the ground gravitationally while smaller particles settle onto vertical surfaces or are circulated by subtle air currents (Nazaroff 2004). Figure 8 illustrates the relationship between air exchange rates and infiltration under two assumed depositions (k) rates (Meng et al. 2005).

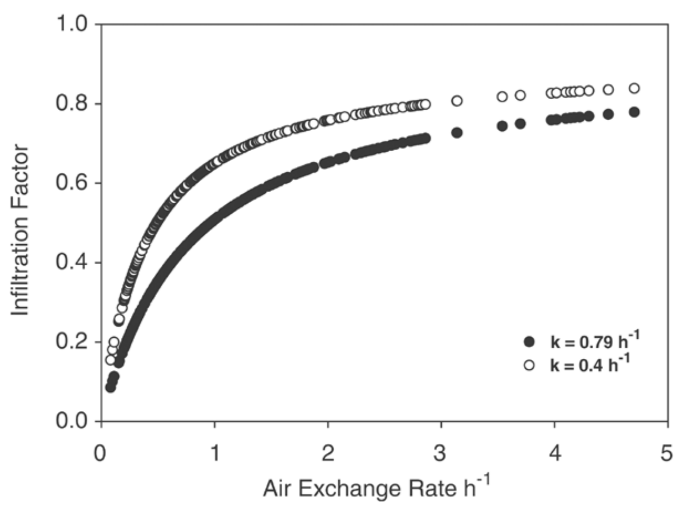

Figure 8. Infiltration factor as a function of air exchange (Meng et al. 2005).

The PTEAM Study (Özkaynak et al. 1996) calculated an average decay rate for $PM_{2.5}$ of 0.39 h^{-1}. Thatcher and Layton (1995) calculated a similar average deposition velocity of 0.46 h^{-1}. Once deposited, re-suspension of particles can also occur as a result of indoor activities. Particles ranging from 1-5µm for example were found to be re-suspended, but only with vigorous activity (Thatcher and Layton 1995).

2.6 Determinants of Residential Infiltration

Infiltration, as a function of penetration, air exchange and deposition, is affected by a number of factors that contribute to the distribution of infiltration factors found both between homes and within homes. Following is an overview of studies that have found associations between infiltration, or the components of infiltration, and housing characteristics, meteorological conditions and residential activities.

2.6.1 Infiltration and Building Characteristics

Residential age is perhaps the foremost housing characteristic that has been examined for its effect on infiltration. Starting in the early 1980's energy efficiency in homes increased due to a variety of regulatory and voluntary measures, which led to significantly tighter home environments (Sherman and Matson 2001). Thornburg et al. (2001) found similar results with older homes having high penetration factors (near 1 for most particle sizes), while newer homes demonstrated significant filtration by the building shell (penetration factors near 0.3). Hanninen et al. (2005b) also found homes built before 1990, included homes that underwent renovation, had average infiltration factors of 0.65+/-0.19 and homes built after 1990 had average infiltration factors of 0.58+/-0.21.

A number of additional housing characteristics have also been associated with infiltration. Sherman and Dickerhoff (1998) found that floor area, number of stories, floor/basement type, and thermal distribution systems all had a significant influence on residential leakage, which is associated with infiltration. Mechanically ventilated structures have also been found to have I/O $PM_{2.5}$ ratios that are significantly less than naturally ventilated structures (Mosley et al. 2001). Chan et al. (2005) found that more expensive homes had tighter envelopes because of better construction and maintenance and identified that leakages from homes with a slab-on-grade foundation were significantly less than homes with a crawlspace or an unconditional basement. Chan et al. (2005) also found that year built along with floor area were the two most significant predictors of leakage, and that older and smaller houses tended to have higher normalized leakage areas compared with newer and larger homes. Low-income houses also have been found to have greater leakage rates than higher-income homes regardless of year built and floor area (Chan et al. 2005). Ozkaynak et al. (1996) found similar results in which house volumes explained a significant component of the relationship between I/O $PM_{2.5}$. Wallace (1996) summarized the published association between volume and indoor $PM_{2.5}$ and found that reductions ranged from -0.75 to 2.0ug/m^3 per 1000 cubic feet.

Few studies have examined specifically the associations between building characteristics and the health effects of $PM_{2.5}$. Spengler et al. (1994) found that respiratory problems had significantly higher odds ratios reported in individuals living in older homes (1.12), homes with smokers (1.24), air conditioners (1.14), air cleaners (1.37), and humidifiers (1.47). Leech et al. (2004) also found that occupants in new energy efficient homes reported more improvements in throat irritation than occupants of traditional homes.

2.6.2 Infiltration and Environmental variables

Meteorological conditions are the major environmental factor affecting residential infiltration. Temperature, rainfall, barometric pressure, relative humidity, wind speed and direction, and elevation all directly influence infiltration through a number of physical processes (Allen et al. 2003; Chang et al. 2003; Chao and Tung 2001). Sherman and Dickerhoff (1998) attempted to broadly account for these environmental influences by creating a correlation factor that accounts for temperature and wind influences, building height (pressure differences due to height), and wind shielding; however, model results were inconsistent.

Meteorological conditions affect infiltration indirectly through the use of residential air conditioning units. Janssen et al. (2002) found that PM_{10} associations with mortality were lower in warm and humid regions of the US compared with milder climate areas, due primarily to different ventilation mechanisms and the use of air conditioners. Opening and closing windows and doors and infiltration through the building shell however are the main mechanisms affecting the amount of outdoor pollution penetrating inside residences. It is important to realize that the use of air conditioners will vary depending on geographic location and could therefore significantly alter infiltration factors and resulting indoor exposures. In this study location, six percent of homes in Seattle have central air conditioning (Janssen et al. 2002) compared with three percent in the CRD (BC Stats, 2002). The dominant parameters controlling residential air exchange for the study population examined here (i.e. mild coastal conditions in the Pacific Northwest) is therefore residents' window opening behaviours.

2.6.2.1 Infiltration and Indoor Activities

A number of indoor activities (e.g. cooking, cleaning or heating) affect the amount of $PM_{2.5}$ generated indoors; however, the main indoor activity that will affect infiltration of $PM_{2.5}$ are window and door opening behaviours and potentially heating and ventilation mechanisms.

Predicting window opening behaviour is extremely difficult and unreliable. Meteorological variables, such as those described previously, are typically used to predict window openings in residences. Probabilistic models derive estimates of windows being open or closed as a function of the presence of an air conditioning system and ambient temperature (Johnson et al. 2004). Johnson et al. (2004) examined factors that affected windows being open or closed for 1100 residences in North Carolina using a visual survey and found the following to increase the likelihood of open windows: occupancy at time of visit, spring season, high population density, dense housing, increasing number of doors, increasing wind speed, increasing number of windows, and absence of air conditioners. Factors found to decrease the likelihood of open windows included: no window screens, February, air conditioner operation, wood exterior, low density housing, clear skies, increasing apparent temperature, low population density. These factors are likely to change between different climate zones and must be interpreted with caution.

2.7 Summary

The majority of epidemiological studies examining the health effects of $PM_{2.5}$ use outdoor concentration estimates from fixed site monitoring stations applied at residential locations to represent personal exposure. Epidemiological studies that use outdoor ambient $PM_{2.5}$ estimates infer that pollution concentrations outside residences are the same as inside residences, or that infiltration in the same for all residences, despite the fact that several studies have shown poor correlation between personal exposures, outdoor ambient concentrations and I/O $PM_{2.5}$ concentrations (Allen et al. 2003; Hanninen et al. 2005b; Janssen et al. 2001; Kousa et al. 2002; Meng et al. 2005; Rea et al. 2001).

Limited research has been conducted that examines $PM_{2.5}$ infiltration in a large number of residences to determine how and why infiltration varies and what effects these variations will have on exposure estimates for epidemiological studies. Recently, Meng et al. (2005) examined residential $PM_{2.5}$ infiltration and found that the use of central site $PM_{2.5}$ as an exposure surrogate underestimates the bandwidth and the distribution of exposures to $PM_{2.5}$ of ambient origin. This corresponds to the large range of infiltration factors found within and between different residences.

This research therefore extends the literature by examining a large sample of residential I/O $PM_{2.5}$ measurements and the associations between $PM_{2.5}$ infiltration, meteorology, residential housing characteristics, and indoor behaviours. An exploratory analysis of a predictive infiltration model based on readily available data for individual residences also is undertaken.

3 Methods

3.1 Research Design

This study was part of the Border Air Quality Study (BAQS), funded by Health Canada through the BC Centre for Disease Control (BC CDC), which examined the impacts of air pollution on pregnant woman and newborn babies in the GBPS airshed (see http://www.cher.ubc.ca/UBCBAQS/welcome.htm). The overall project involves researchers from the University of Washington, the University of British Columbia and the University of Victoria.

The research reported here was conducted in two locations within the GBPS airshed. Figure 9 illustrates the two study locations (Victoria and Seattle) within the GBPS airshed.

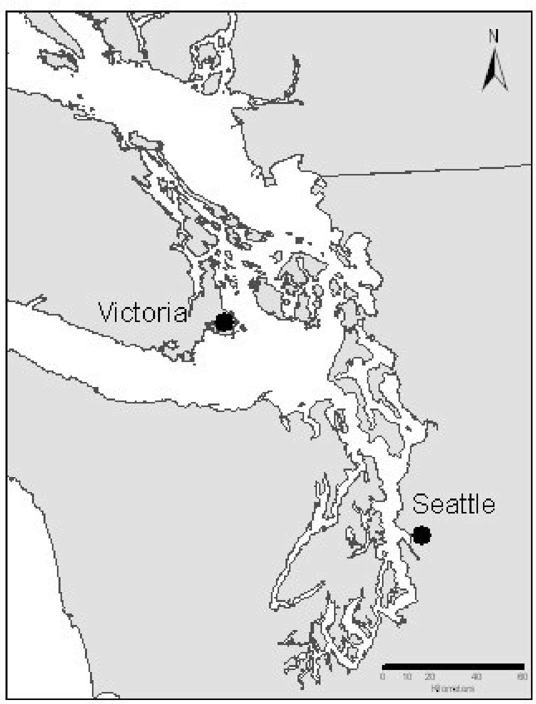

Figure 9. GBPS airshed including Seattle and Victoria (CRD) sample locations.

A new I/O $PM_{2.5}$ monitoring campaign was established in the CRD to examine I/O $PM_{2.5}$ differences and to determine residential infiltration. The new monitoring data were combined with previous monitoring data obtained in Seattle Washington.

3.2 CRD Residential Sampling Methodology

A monitoring campaign was established in the CRD to examine a sample of residential I/O $PM_{2.5}$ measurements and infiltration factors. The sample was not representative of all homes in the CRD, but was selected purposively to maximize the spatial variability of homes and to include specific housing characteristics that would refine and address specific gaps in the Seattle sample (such as the lack of homes monitored in the heating (October to February) and non-heating (March to September) seasons and specific housing characteristics).

A number of different methods were used to recruit study residences. An email campaign and two newspaper articles (one in the Vancouver Island Newsgroup papers and one in the University of Victoria Ring paper) were the main residential recruiting mechanisms. Individuals interested in participating in the study responded to the email or newspaper articles and provided their residential address and answered a short screening questionnaire. The questionnaire asked whether smoking occurred in their home, and the type, age, size, and location of their residence. This information was then used to select forty residents for monitoring. One hundred and seven homes responded to the initial recruitment campaigns.

Ethical approval was gained through the University of Victoria's ethics department for monitoring in the CRD and for obtaining the monitoring data from the Seattle study. Appendix 1 provides the research ethics board certificate of approval for both studies and Appendix 2 provides the consent form that was completed by each participant in the CRD portion of the study.

3.3 CRD Residential Sample

Forty residences were selected purposively to participate in the CRD monitoring campaign during 2006. These homes represented non-smoking households, since the primary purpose of this study was to examine factors affecting infiltration of ambient $PM_{2.5}$. Homes with environmental tobacco smoke (ETS) are dominated by this source and infiltration factors cannot be calculated. The sample was purposive and the main sampling criteria were residential type stratified by detached homes and apartments and condominiums, and age of construction. These criteria addressed shortcomings to the Seattle residential sample.

Table 2 summarizes the characteristics of the sample and Figure 10 illustrates the location of these residences in the CRD. Brackets indicate the number of homes that were monitored twice. Seven monitoring events had to be removed due to monitoring error, which will be explored later on in the data analysis chapter.

Table 2. Summary of residential sample in the CRD.

	Private homes	**Apart /Condos**	**Total residences**	**Total Events**
Total monitored	30(27)	8(8)	38	73
Season				
- Heating (Oct-March)	27	6(1)	33	33
- Non heating (Apr-Sept)	30	8(1)	38	39
- Both	27	6	33	33
Age of residence				
< 1940	6(4)	0	6	10
1940-1959	5(5)	0	5	10
1960-1974	7(7)	2(2)	9	18
1975-1989	7(7)	4(4)	11	22
>1990	5(4)	2(2)	7	13

() homes monitored twice.

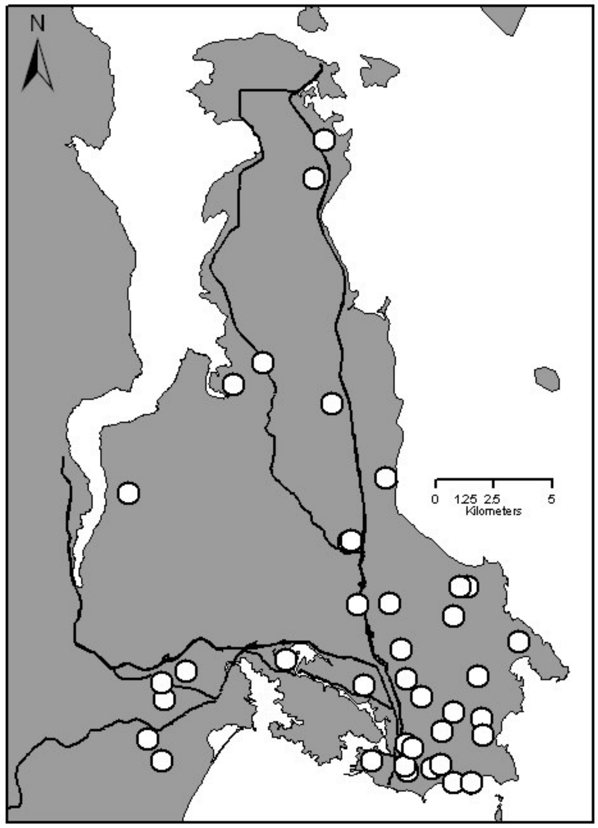

Figure 10. Location of monitored homes in the CRD.

3.4 Seattle Residential Sample

Monitoring data for Seattle Washington were compiled from previous research undertaken between 1999 and 2001 that were part of a health panel study examining the affects of $PM_{2.5}$ on individuals with chronic obstructive pulmonary disease (COPD) (Liu et al. 2003). Sixty two residential monitoring sessions were compiled from forty six different residences. Table 3 illustrates the Seattle monitoring sample and Figure 11 shows the location of monitored residences in Seattle.

Table 3. Summary of residences monitored in Seattle from 1999-2003.

	Private homes	**Apart /Condos**	**Total residences**	**Total monitoring events**
Total monitored	25(11)	21(5)	46	62
Season				
- heating (Oct-March)	19(2)	14	33	34
- non heating (Apr-Sept)	6(9)	10(2)	16	27
- both	6	5	11	11
Age of residence				
< 1940	6(3)	3(1)	9	13
1940-1959	13(5)	2	15	20
1960-1974	4(1)	3(1)	7	9
1975-1989	1(1)	7(3)	8	12
>1990	1(1)	6	7	8

() homes monitored twice.

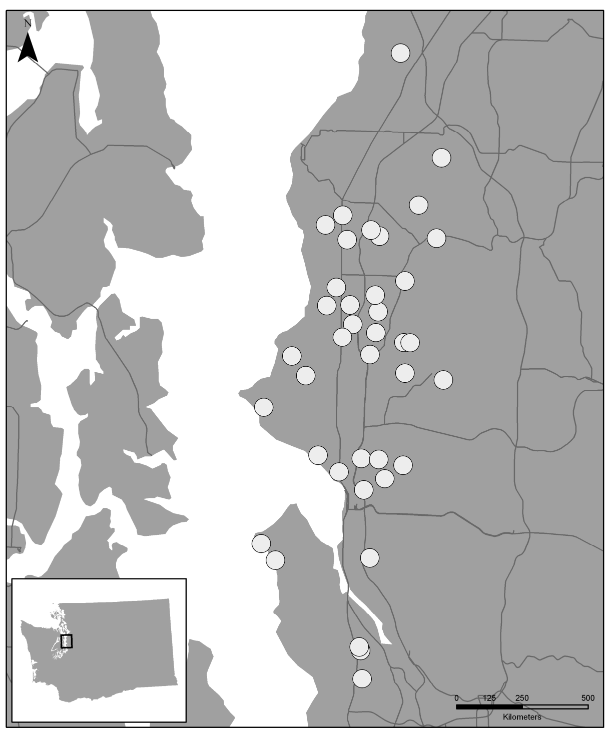

Figure 11. Location of monitored residences in Seattle.

The combined residential monitoring sample from the CRD and Seattle is 135 monitoring events for 84 different residences. The two samples used identical monitoring methods, as will be discussed in the following chapter.

3.5 Monitoring Methodology

The Seattle monitoring protocol (Allen et al. 2003) was replicated in the CRD to ensure compatibility between the two residential samples. Monitoring was conducted using Radiance A903 Nephelometers (hereafter referred to as Nephs). Nephs operate on the principle of light scattering, a lamp flashes inside a matt-black tube and particles suspended in the air are detected, amplified and displayed (see Figure 12). Nephs are particularity sensitive to small combustion particles, corresponding to $PM_{2.5}$. Nephs were placed inside and outside each residence for durations of five days (CRD sample), while monitoring duration in Seattle included both five and ten day intervals.

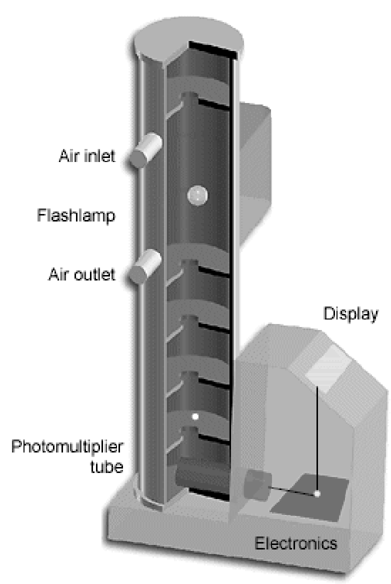

Figure 12. Diagram of Radiance A903 Nephelometer.

Exposure studies have shown that infiltration factors change within a residence (Meng et al. 2005); however, the literature reveals no consensus as to the timeframe needed to capture average infiltration factors. Riain et al. (2003) examined the amount of time it took for I/O PM ratios to reach within five percent of long-term I/O ratios, and found that the time ranged from twenty hours to ten days. In the absence of a proven timeframe needed to capture average infiltration factors, five days was selected as the monitoring time frame. Ryan Allen was a lead investigator in monitoring and analyzing the Seattle I/O $PM_{2.5}$ data and confirmed that five days was satisfactory for determining infiltration factors (personal communication, 2006). A five-day monitoring period will likely capture more than one meteorological episode, as meteorological events tend to last a maximum of five days. The five day monitoring period was also established to capture both weekend and weekday conditions whenever possible.

The Nephs recorded light scattering measurements every five minutes to provide a time-series over the five day monitoring period. The light scattering values were converted into $PM_{2.5}$ using an equation calculated by running a Neph next to a fixed site Tapered Element Oscillating Microbalance (TEOM) station (an accepted instrument for measuring $PM_{2.5}$). Equation 2 was determined in the Seattle study and was used to convert both the Seattle and CRD light scattering data to $PM_{2.5}$ to ensure compatibility.

EQ2: $PM_{2.5} = [((Light\ scatter*100{,}000)-0.01)/0.28]$

One limitation of using light scattering data to represent $PM_{2.5}$ mass is that the size, shape and composition of particles will affect the amount of light scattered by the Nephs. Using a single conversion factor for both I/O light scattering measurements assumes that particle size and composition are equal inside and outside a residence. Allen et al. (2006) found that using a constant light scattering to mass relationship had a very small impact on infiltration estimates.

Monitoring occurred at a central location within each residence and at a secure location outside each residence. The outdoor monitor was located within a locked box and drew air through an intake tube. Each residence was monitored during both the heating (October to March) and non-heating (March to September) seasons to capture the influence of seasonality, which has been highlighted as a research shortcoming in previous work (Dockery and Spengler, 1981a; US National Research Counsel 2001; Wallace et al. 2003).

During monitoring, residents completed an activity log to record personal activities in the residence at half hour intervals. This was the smallest interval thought to limit the time required by residents to complete the daily activity logs, while still capturing the variability of short term events (e.g. cooking or cleaning). A sample activity log is shown in Appendix 3.

Residential surveys were also completed for each monitoring event. The survey collected information on housing characteristics and general indoor behaviours that could affect indoor $PM_{2.5}$ generation and infiltration. For example, $PM_{2.5}$ infiltration may be influenced indirectly by socioeconomic status (SES) of the residents, or the number and type of windows in a residence. The survey data were also used to examine the accuracy of property assessment data and in cases where assessment data were not available were used as a replacement. The residential survey is shown in Appendix 4.

3.6 Developing a GIS for Infiltration Modeling

Currently, the main limitation of indoor exposure methods for $PM_{2.5}$ is that they cannot feasibly be applied to a large number of residences. A major challenge facing research examining infiltration of ambient $PM_{2.5}$ has been obtaining information on the factors affecting infiltration, specifically infiltration differences resulting from building characteristics. This section reviews the GIS data available for modeling $PM_{2.5}$ and the process of collecting and formatting data for both Seattle and the CRD.

3.6.1 Housing Characteristics-Spatial Property Assessment Data (SPAD)

This research makes use of SPAD to examine the relationships between infiltration and residential building characteristics. SPAD is made up of property assessment data and the spatial information showing where each property is located (cadastral data). Property assessment data generally include information on individual building characteristics, building and land values and land-use information. Table 4 indicates the variables identified within the two sample regions SPAD that may be used for $PM_{2.5}$ infiltration modeling.

Table 4. SPAD variables that may be used in a regional infiltration model.

Land Variables	Property Size, Property Use, Topography, Building Permit
Building Variables	Improvement Type, Structure Use, Building Type, # of Stories, Year Built, Total Square Footage, Condition of Building, # of Rooms, Predominant Heating Type, Fireplaces, Structural Quality, Improved Value, Land Value.

Not all variables collected in SPAD are intuitive. Condition is a variable that is assessed based on the condition of the building structure only. Structural quality is a similar variable; however, condition focuses on more cosmetic features, such as paint and siding condition, while structural quality focuses only on the actual building structure. Improved value is the value assinged to the building structures of a property only and is independent of land value.

SPAD was collected for both study areas since the final infiltration model will be created from both the Seattle and CRD samples. Spatial property assessment data were readily available for the US portion of the study region (free to download or order depending on Counties) while in BC the data were much harder to obtain. Washington State property assessment data and cadastral data are developed and stored within each County, while in BC the assessment authority collects property assessment data and each jurisdiction develops and houses its own cadastral data. Figure 13 illustrates the difference in the development and storage of SPAD between the two regions. Cadastral data had to be collected directly from every municipality (n=27) in the Canadian portion of the GBPS airshed and academic sharing agreements had to be developed before most municipalities would share the data. The process of collecting the cadastral data for the Georgia Basin took approximately four months. The property assessment data also had to be purchased from the BC Assessment Authority.

An example of cadastral data for downtown Victoria is shown in Figure 14. The CRD SPAD data contains approximately 102,000 records. The counties encompassing the Seattle study area include King County with 573,000 records and Snohomish County with 259,000 records.

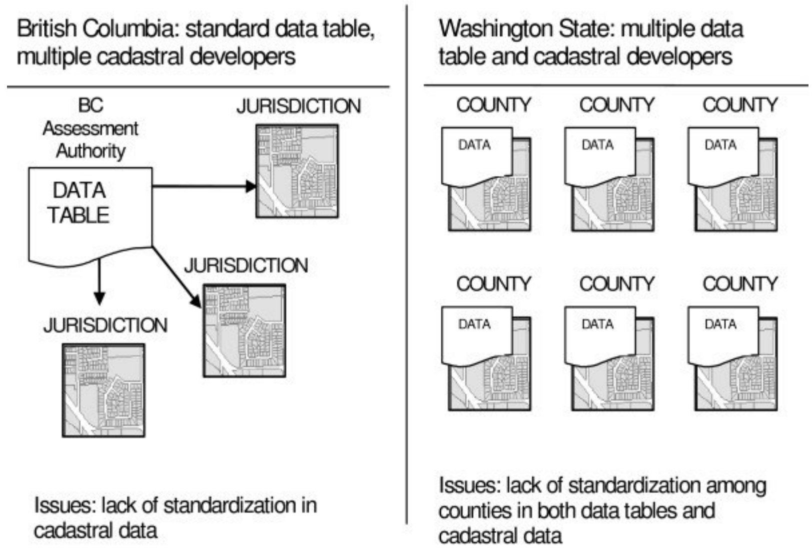

Figure 13. Comparison of Washington and BC SPAD (Setton et al. 2005).

Figure 14. Cadastral data for a portion of downtown Victoria.

Linking cadastral data to property assessment data was the first step undertaken to create a spatial coverage that could be used to investigate residential infiltration. King and Snohomish County cadastral data, for Seattle, had different data formats and identifiers that had to be standardized. For example, King County cadastral data were separated into different commercial and residential classes. Residential cadastral data therefore had to be merged before being linked with property assessment data.

Different building attributes were collected in the property assessment data for King and Snohomish County and the CRD. A standardized set of variables were developed for detached residences, apartments and condominiums. These variables were identified in the literature as having a potential influence on infiltration and indoor $PM_{2.5}$ levels. The datasets from the three assessment authorities were formatted and cleaned to those variables presented earlier in Table 4. Housing values were standardized to Canadian dollars using an exchange rate of 0.83, which was the average exchange rate during 2005 when the assessment data were collected (Royal Bank, 2007). The average improved value of all detached homes in Seattle was $145,267 (Cdn) and in Victoria was $120,177. The average total value of homes in Seattle was $201,352 (Cdn) and in the CRD was $323,219. Quartiles of improved and total values for each house could also have been created from the average housing values in each area.

Property assessment data in Seattle also contained more detail on all residential types than did the BC property assessment data. SPAD in BC collected detailed building characteristics for detached homes only and collected data for entire buildings, rather than units, for such buildings as apartments of condominiums. On the other hand, King County collected detailed data for detached residences as well as for each apartment and condominium unit.

There are inherent limitations to using SPAD to represent building characteristics. Firstly, all building characteristics that may affect infiltration are not included in SPAD. These include such variables as storm windows, air conditioning (not present for King

County or CRD SPAD), building materials, and presence of general heating, ventilation and air conditioning systems (HVAC). Fortunately, due to the mild climate in the study region, few residences have HVAC systems. BC Stats (2002) reported that only 3.3% of residences have air conditioners in the CRD and Janssen (2002) reported that 6% of homes in Seattle have air conditioning units. The second major limitation of SPAD is that property upgrades may not be represented in the data. Assessors do regularly update data for taxation purposes but it is unlikely that all upgrades will be identified. Thirdly, property assessments also vary between different regions, requiring data to be standardized and formatted before counties and assessment regions can be amalgamated.

3.6.2 Environmental Variables

Meteorological conditions were collected for each monitoring event in Seattle and the CRD. Data in Seattle were compiled from the nearest fixed site meteorological station with an average distance of 9km between the monitored residences and the meteorological station. The resolution of meteorological data in Victoria was much finer with an average distance between monitored residences and meteorological site of 0.87km. A dense network of meteorological stations was available in Victoria as part of a separate research program that installed meteorological stations at schools throughout the area (see http://www.victoriaweather.ca/). Figure 15 illustrates the location of meteorological monitoring station and the location of monitored residences in the CRD

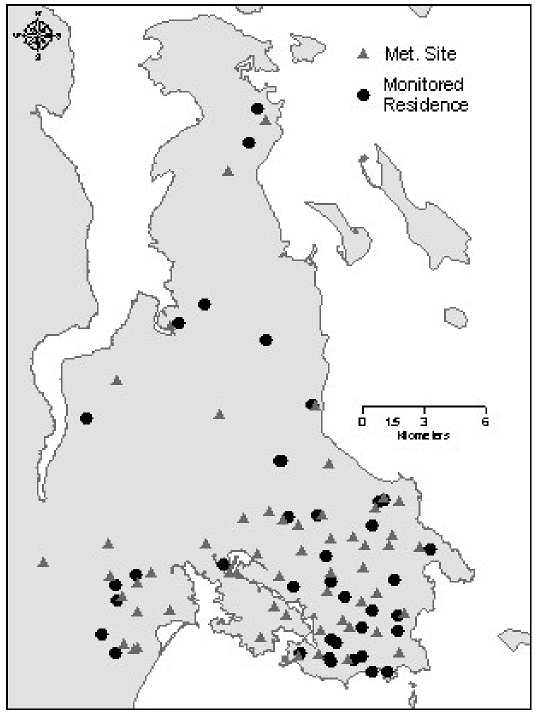

Figure 15. Meteorological stations and monitored residences in the CRD.

4 Data Analysis

4.1 Quality Control of Monitoring Data

Adjustments to each Neph were made based on "between instrument" calibrations to ensure that each monitor was correctly measuring light scattering. Nephs are relatively stable monitoring devices; however, baseline drifts can occur that significantly alter data accuracy. Monitors were run side by side for a minimum of twelve hours to ensure data quality and to compare measurements between monitors. Baseline drifts in Neph measurements were corrected using linear regression. Figure 16 shows an example of the four co-located monitors, the relationships between monitors (UBC r^2=0.978 and UVIC r^2=0.996) and a baseline drift in monitor UBC_In.

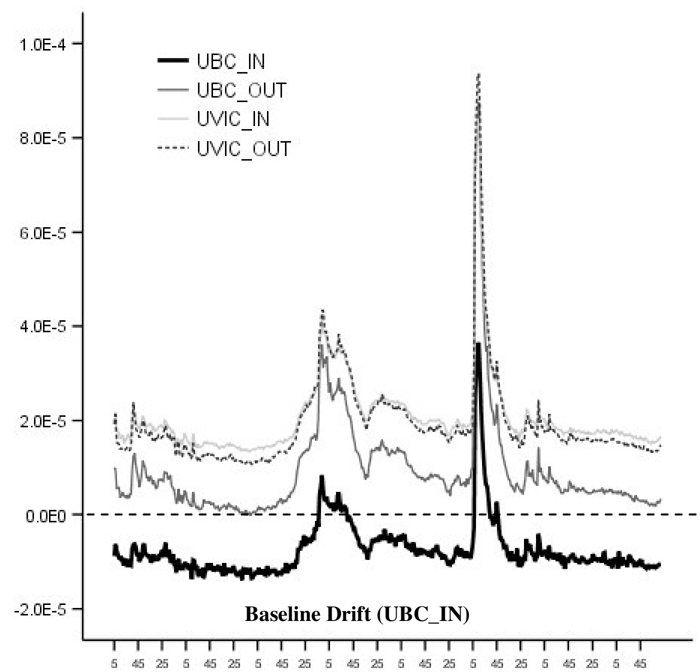

Figure 16. Example of co-located monitors and baseline drift.

Monitors are named UVIC and UBC because one set of monitors was purchased by UVIC specifically for this project and the other set was borrowed from UBC. During calibration paired monitors were adjusted to the indoor monitor as the dependent variable, and if all monitors were present in calibration the adjustments were made to the indoor UVIC monitor. If the r-squared between paired monitors was less than 0.90, the monitors were adjusted with particle free air and h324-refig gas (known scattering coefficient of $8.44 \times 10^{-5} m^{-1}$). Appendix 5 summarizes correlations during Neph calibrations in the CRD.

Extensive quality control measures were conducted to ensure reliability of the residential I/O $PM_{2.5}$ data (same quality control used in the Seattle study), which led to the removal of several events from analyses. Seven monitoring events were removed due to equipment malfunction or unreliable results, leaving 73 events available to examine residential I/O $PM_{2.5}$. Additional quality control criteria were applied to the I/O $PM_{2.5}$ data before infiltration could be calculated to ensure that low level indoor $PM_{2.5}$ sources were removed. Negative Neph measurements were removed and each monitoring event had to meet the following criteria (replicated from the Seattle Study):

(1) achieve 50% data collection;

(2) have a significant ($p < 0.05$) indoor to outdoor relationship during non-source periods (23:00 to 6:00); and

(3) have a median indoor to outdoor ratio < 1 during non-source periods (23:00 to 6:00).

Appendix 6 summarizes the above criteria for each monitoring event and indicates those events that did not meet all criteria, which led to twelve monitoring events being removed, leaving 61 monitoring events for the infiltration analysis. The number of excluded monitoring events in the CRD corresponded to the number removed in the Seattle study.

4.2 Calculating Infiltration

The recursive mass balance model was used to calculate residential infiltration (from Allen et al. 2003). EQ3 was solved for the constants a_1 and a_2 from the continuous indoor and outdoor light-scattering data and then applied to EQ4.

EQ3: $$(b_{sp})_t^{in} = a_1(b_{sp})_t^{out} + a_2(b_{sp})_{t-1}^{in} + S_t^{in}$$

EQ4: $$F_{inf} = \frac{a_1}{1 - a_2}$$

b_{sp} is the coefficient representing the light scattering data collected by the Nephs. b_{sp}^{in} represents the indoor light scatter value at time t, which is a function of $(b_{sp})^{out}$ at time t multiplied by a_1 (penetration coefficient of outdoor particles indoor) and $(b_{sp})^{in}$ at time t-1 (decay factor) multiplied by a_2 (deposition of indoor particles once indoors), and S^{in} (indoor generated $PM_{2.5}$ at time t).

All indoor sources of $PM_{2.5}$ (the S^{in} term in Equation 3) first had to be removed before a_1 and a_2 could be calculated. These sources include such activities as cooking, cleaning or heating. If indoor generated $PM_{2.5}$ are not removed they artificially inflate infiltration estimates because the indoor generated $PM_{2.5}$ will be classified as infiltrated ambient $PM_{2.5}$. The methods for censoring indoor generated $PM_{2.5}$ were replicated from the Seattle study (Allen et al. 2003) and are explained in the following section.

4.2.1 Censoring Indoor Sources of $PM_{2.5}$

To calculate residential infiltration, all indoor generated $PM_{2.5}$ must first be removed or censored. Infiltration can be calculated from unoccupied homes to ensure that all $PM_{2.5}$ inside a home originated from ambient $PM_{2.5}$; however, valuable information about occupied residential infiltration and indoor sources can be gained by monitoring residences under regular conditions. Figure 17 illustrates I/O $PM_{2.5}$ data before indoor sources have been removed. A spike in the indoor time-series generally represents a large indoor source. Opening windows typically results in gradual indoor $PM_{2.5}$ increases up to the $PM_{2.5}$ outdoor level.

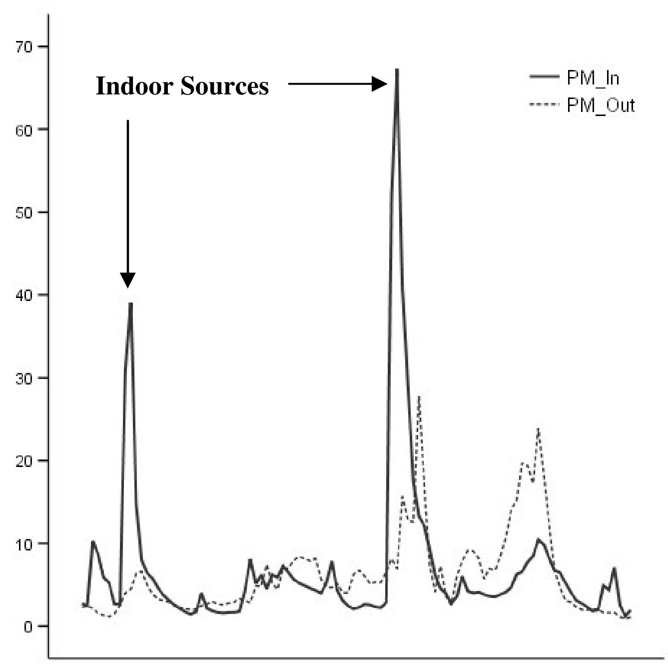

Figure 17. Example of indoor sources and resulting $PM_{2.5}$ increases.

Censoring indoor sources was conducted on the light scattering (b_{sp}) data. Indoor b_{sp} levels that increased rapidly without corresponding changes in the outdoor b_{sp} levels were identified using EQ5 and then removed or modified (Allen et al. 2003). EQ5 can also be modified by lowering the difference between points (1.5 to 1.3 or 1.1) to identify smaller indoor sources of $PM_{2.5}$.

EQ5: $$\frac{bsp^{in}_{t}}{bsp^{in}_{t-1}} \geq 1.5 \quad and \quad \frac{bsp^{out}_{t}}{bsp^{out}_{t-1}} \leq 1.5 \quad and \quad ((bsp)^{in}_{t} - (bsp)^{in}_{t-1}) \geq 10^{-5} (or \sim 4ug/m^3)$$

$b_{sp}^{in/out}$ at time t represents the difference between indoor and outdoor light scattering and $b_{sp}^{in/out}$ at time t-1 represents light scattering data for the previous hour. If the indoor b_{sp} levels increased more than 4ug/m^3 per hour they were also removed (Allen et al. 2003).

Creating a consistent censoring procedure was important to calculate reliable infiltration factors. The censoring technique described above was compared to the indoor time activity logs to test whether indoor sources were in fact being removed. The censoring algorithm correctly removed approximately ninety percent of recorded indoor activities, and the remaining ten percent of recorded indoor sources did not elevate indoor levels to the censoring threshold.

5 Results

First, the results of the I/O $PM_{2.5}$ monitoring campaign for the CRD are presented in Chapter 5.1. Differences between I/O $PM_{2.5}$ are examined as well as I/O $PM_{2.5}$ ratios, temporal patterns and determinants of I/O $PM_{2.5}$. Next, Chapter 5.2 examines residential infiltration for both the CRD and Seattle samples and presents the results of an infiltration model incorporating meteorological variables and housing characteristics from SPAD.

5.1 CRD Residential $PM_{2.5}$ Analysis

Indoor and outdoor $PM_{2.5}$ were examined in the CRD to evaluate outdoor $PM_{2.5}$ as a proxy for indoor total exposure and to identify factors affecting the relationship between I/O $PM_{2.5}$. The monitoring data collected in the CRD during 2006 provided new data to address these questions.

5.1.1 CRD I/O Residential $PM_{2.5}$

Seventy three monitoring events in the CRD contained reliable I/O $PM_{2.5}$ data, which are summarized in Table 5. Fifty-seven monitoring events were completed for detached homes and sixteen for apartments and condominiums. Thirty three residences were monitored during both the heating and non-heating seasons.

Table 5. Summary of residences monitored in the CRD during 2006

	Detached homes	**Apartments /Condos**	**Total residences**	**Monitoring events**
Total monitored	30(27)	8(8)	38	73
Season				
- Heating (Oct-March)	27	6(1)	34	34
- Non heating (Apr-Sept)	30	8(1)	38	39
- Both	27	6	33	33

In total, 9,502 pairs of one hour I/O $PM_{2.5}$ measurements were collected. The association between all one hour I/O $PM_{2.5}$ measurements was weak (r^2=0.04, p=0.498). Figure 18 illustrates the association between all one hour I/O $PM_{2.5}$ and Figure 19 illustrates the relationship between one hour I/O $PM_{2.5}$ from 23:00 to 6:00, when indoor sources of $PM_{2.5}$ are minimal. During this period the association between I/O $PM_{2.5}$ increased (r^2=0.335, p<0.000), which is expected since the majority of indoor sources, such as cooking, cleaning or heating, are not present.

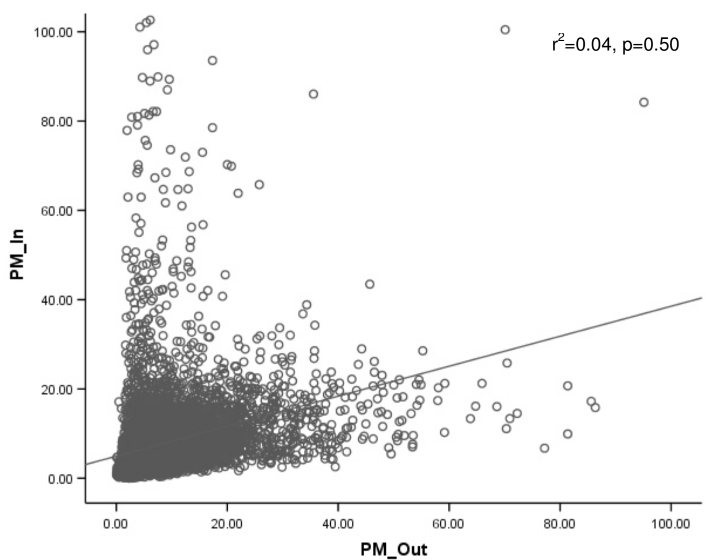

Figure 18. Hourly I/O $PM_{2.5}$ for all CRD monitoring events.

The five days mean I/O $PM_{2.5}$ levels are more representative of longer term averages since anomalous events will have less impact when averaged over the five days monitoring period. The mean five days indoor level of $PM_{2.5}$ for the 73 monitoring events was 7.90ug/m^3 and outdoors 8.45ug/m^3.

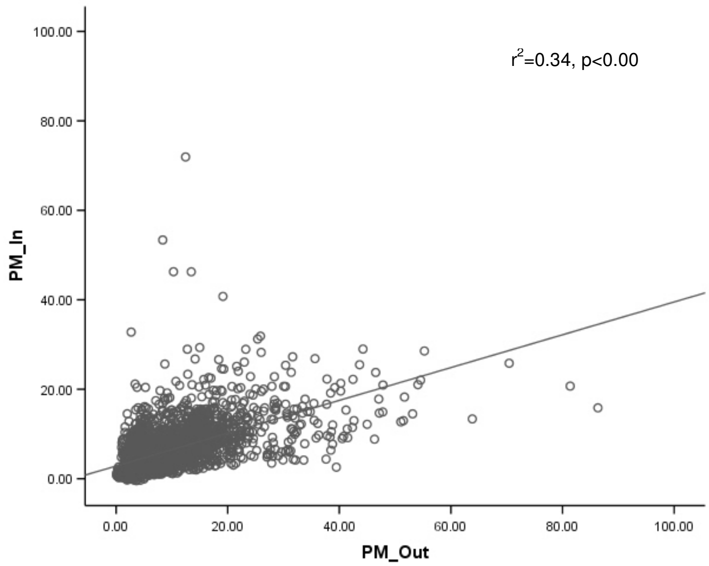

Figure 19. Hourly I/O $PM_{2.5}$ for CRD monitoring events from 23:00 to 6:00.

Table 6 illustrates the distribution of the five days I/O $PM_{2.5}$ data. Figure 20 also illustrates the mean I/O $PM_{2.5}$ relationship (r^2=0.312, p<0.000). Thirty homes had mean indoor $PM_{2.5}$ greater than outdoor $PM_{2.5}$ levels. Appendix 7 summarizes the I/O $PM_{2.5}$ data for each of the 73 monitoring events.

Table 6. Summary of I/O $PM_{2.5}$ measurements in the CRD.

	Mean	**Med.**	**SD**	**10th**	**25th**	**75th**	**90th**
Indoor $PM_{2.5}$	7.90	6.94	3.90	3.64	5.30	10.55	13.14
Outdoor $PM_{2.5}$	8.45	8.22	3.77	4.29	5.56	10.16	13.17

The five days I/O $PM_{2.5}$ data, shown in Figure 21, are normally distributed. Short term I/O $PM_{2.5}$ sources caused the distributions to be slightly positively skewed, while one hour distributions are highly skewed.

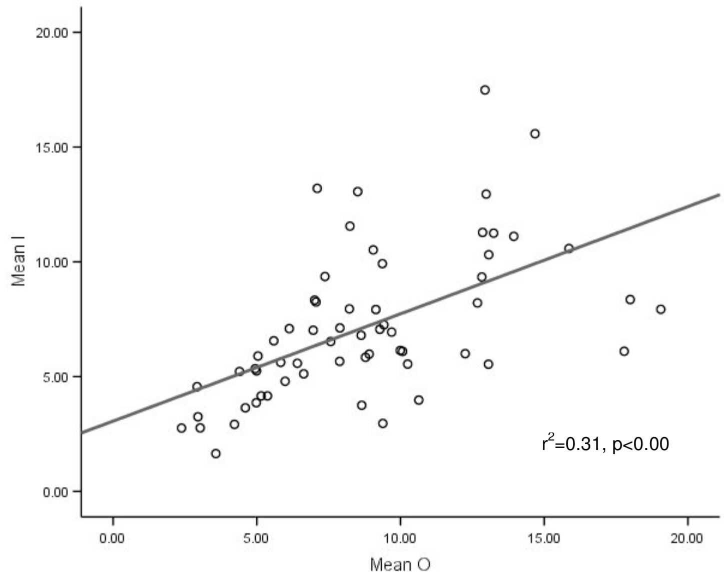

Figure 20. CRD five day mean residential I/O $PM_{2.5}$.

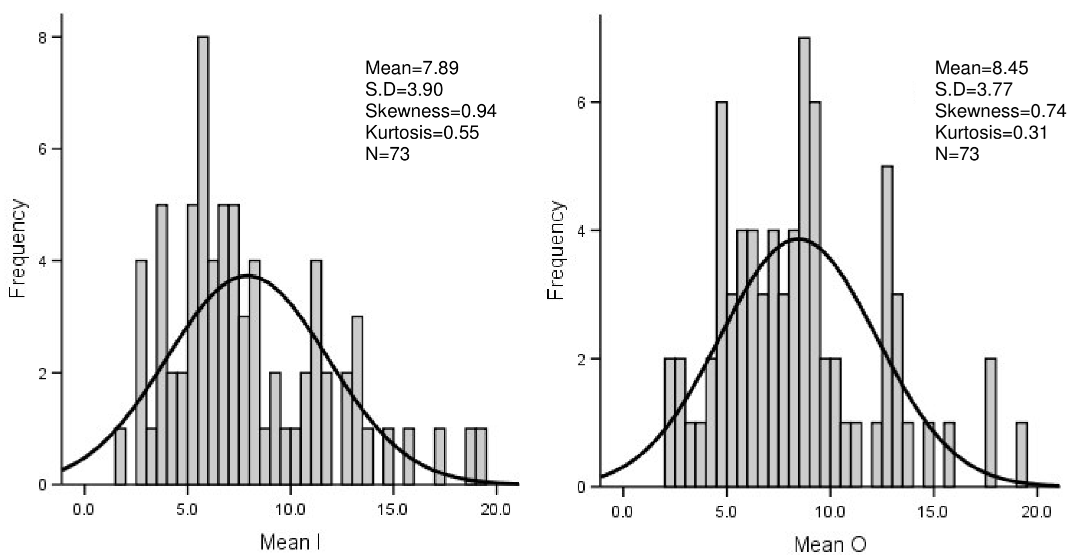

Figure 21. Distribution of five day mean residential indoor and outdoor $PM_{2.5}$.

5.1.2 Residential I/O $PM_{2.5}$ Ratios

The mean five days I/O $PM_{2.5}$ ratio in the CRD was 1.03+/-0.54 and the average one hour mean ratio was 1.33+/-0.75, which are summarized in Table 7. During non-source periods (23:00 to 6:00) the mean one hour I/O $PM_{2.5}$ ratio was 0.87. Figure 22 illustrates the spatial distribution of the five day I/O ratios in the CRD.

Table 7. Five day and one hour residential I/O $PM_{2.5}$ ratios.

	Mean	**Med.**	**SD**	**10th**	**25th**	**75th**	**90th**
5 day I/O ratios	1.03	0.89	0.54	0.46	0.71	1.19	1.61
1 hour I/O ratios	1.33	1.18	0.75	0.64	0.87	1.53	2.30

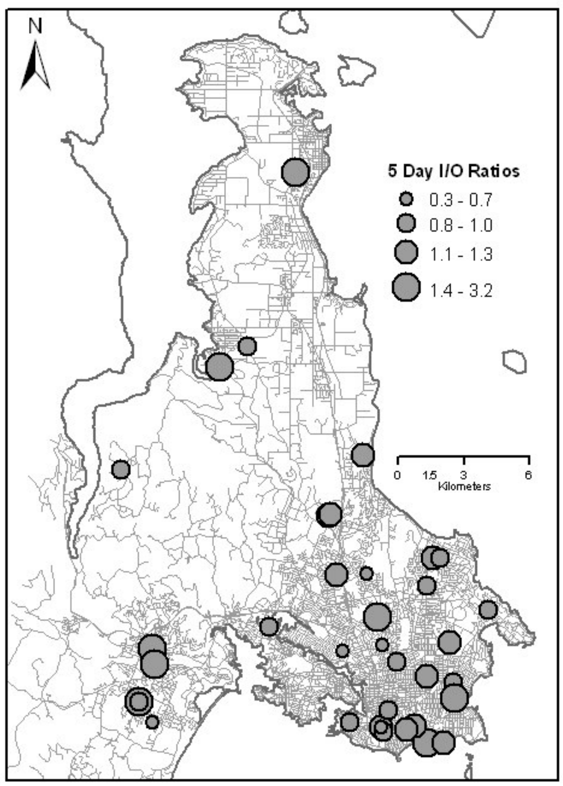

Figure 22. Five day I/O $PM_{2.5}$ ratios in the CRD.

No spatial clustering was identified for the I/O $PM_{2.5}$ ratios in the CRD. The Moran's I statistic was calculated in ArcGIS to examine spatial clustering of the I/O

$PM_{2.5}$ ratios. The resulting Morans I index (Z=-0.06) indicated that the I/O $PM_{2.5}$ ratios in the CRD were random. Clustering at the p=0.10 level is represented by a Morans I index Z-values of +/-1.96. This result suggests that outdoor $PM_{2.5}$ is not driving I/O $PM_{2.5}$ ratios and that housing characteristics, individual behaviours, and seasonality are largely responsible for I/O $PM_{2.5}$ differences in the CRD. Examining one hour $PM_{2.5}$ ratios, which were available due to the continuous Neph measurements, provided additional information on how the relationship between I/O $PM_{2.5}$ changes temporally with different I/O $PM_{2.5}$ sources. Seasonal variation also existed due to changing outdoor $PM_{2.5}$ levels.

5.1.3 Seasonality and Residential I/O $PM_{2.5}$ Ratios

Outdoor $PM_{2.5}$ varied through the year due to changing sources of ambient $PM_{2.5}$ and meteorological conditions. The largest change in outdoor $PM_{2.5}$ was between the heating and non-heating seasons, due primarily to residential wood heating in the CRD, which is a substantive component of $PM_{2.5}$ emissions during the heating season. The changing levels of ambient $PM_{2.5}$ affected indoor residential levels as a large percentage of indoor $PM_{2.5}$ originates outdoors. Figure 23 illustrates average I/O $PM_{2.5}$ changes for each month through 2006 for the 73 monitoring events in the CRD. Large variations between indoor and outdoor levels (such as in December) may be the result of small sample sizes and should be interpreted with caution.

Stratification based on a heating and non-heating season variable was used to examine the general effects of residential wood heating and meteorology on residential I/O $PM_{2.5}$. Table 8 indicates the effects of changing outdoor $PM_{2.5}$ levels and meteorology on indoor residential $PM_{2.5}$.

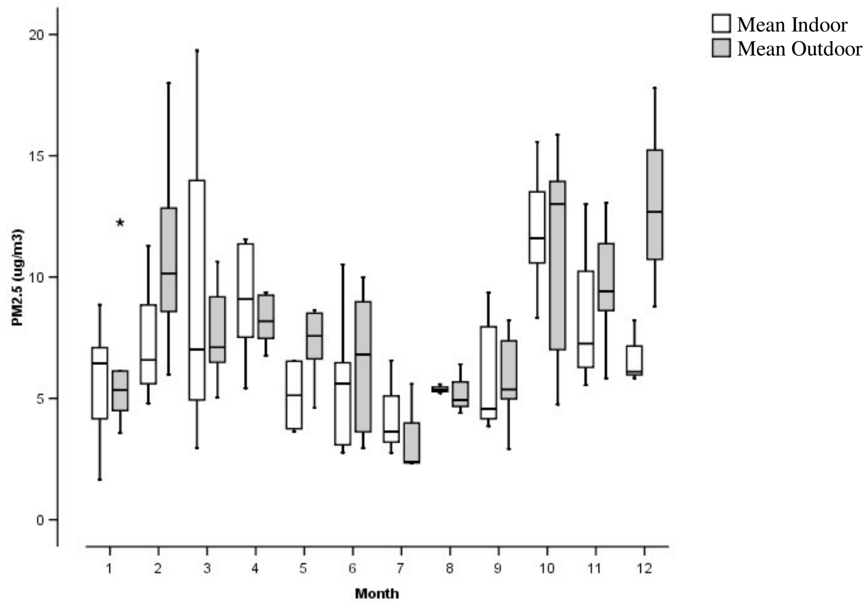

Figure 23. Monthly I/O $PM_{2.5}$ levels in the CRD (where 1=Jan., 2=Feb., etc.).

Table 8. Heating season (HS) and non-heating season (NHS) I/O $PM_{2.5}$.

	Mean	**Med.**	**SD**	**10^{th}**	**25^{th}**	**75^{th}**	**90^{th}**
HS Indoor $PM_{2.5}$	8.56	7.93	3.62	5.84	5.84	11.25	13.21
NHS Indoor $PM_{2.5}$	7.29	6.06	4.11	2.96	4.11	9.50	13.36
HS Outdoor $PM_{2.5}$	*10.16**	*9.69**	*4.19**	*4.89**	*6.02**	*13.1**	*16.6**
NHS Outdoor $PM_{2.5}$	*6.87**	*7.08**	*2.48**	*2.95**	*4.98**	*8.72**	*9.45**
HS 5 days I/O Ratio	0.96	0.79	0.58	0.45	0.65	1.16	1.73
NHS 5 days I/O Ratio	1.10	1.06	0.51	0.60	0.78	1.29	1.64
HS 1 hour I/O Ratio	1.33	1.09	0.80	0.66	0.88	1.47	2.76
NHS 1 hour I/O Ratio	1.32	1.24	0.73	0.60	0.84	1.60	2.06

*Significant difference (p<0.05)

A significant difference existed between mean outdoor $PM_{2.5}$ levels in the heating and non-heating seasons in the CRD (p=0.01). During the winter, the average five days I/O $PM_{2.5}$ ratio was 0.96, while in the summer it was 1.10. The indoor concentration however remained higher in the winter due to the large increase in outdoor $PM_{2.5}$ levels (10.16 versus 6.87ug/m^3). One hour I/O $PM_{2.5}$ ratios between the two seasons were not significantly different (p=0.44), which is likely due to the increased contributions of indoor sources during the heating season when air exchange rates are low.

5.1.4 Diurnal Changes of I/O Residential $PM_{2.5}$

Indoor and outdoor $PM_{2.5}$ also had significant temporal trends. Figure 24 illustrates the diurnal change in all residential one hour I/O $PM_{2.5}$ data for 2006.

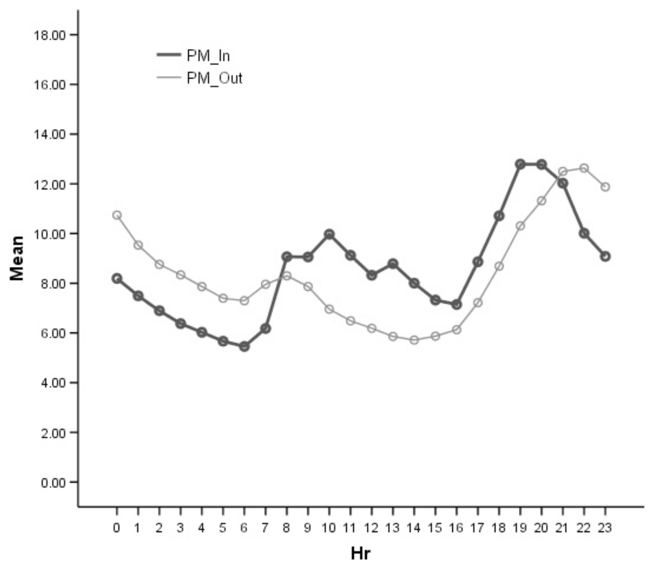

Figure 24. Diurnal changes in residential I/O $PM_{2.5}$.

Outdoor $PM_{2.5}$ was greater than indoor $PM_{2.5}$ from 21:00 to 7:00. The greatest differences between I/O $PM_{2.5}$ occurred from 10:00 to 12:00. This difference is due largely to decreasing outdoor $PM_{2.5}$ levels while indoor sources continued to elevate indoor $PM_{2.5}$ levels. The range of hourly indoor $PM_{2.5}$ also changed significantly throughout the day, corresponding to time periods when indoor activities were high. Figure 25 illustrates the hourly mean and 95% confidence interval for all indoor monitoring data. The confidence intervals were calculated by SPSS and were used instead of standard deviations because the numbers of samples within each hour, or similarly within each day or month as shown later, are not uniform. The confidence intervals are useful for illustrating the variability of $PM_{2.5}$ and the range in which the $PM_{2.5}$ levels are likely to fall within.

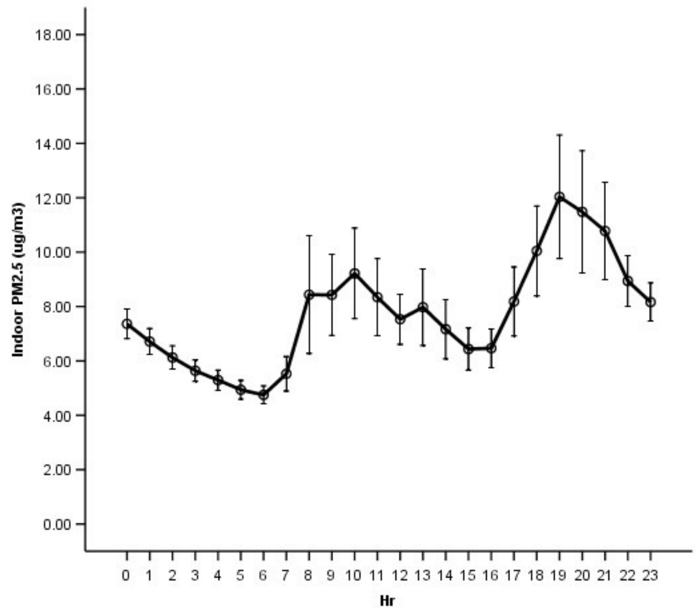

Figure 25. Hourly Indoor $PM_{2.5}$ with 95% confidence intervals.

During the night, confidence intervals are small, while during morning and evening periods when cooking and other indoor activities are frequent, the confidence intervals are large, reflecting the variability of indoor $PM_{2.5}$ concentrations due to indoor behaviours and resulting indoor generated $PM_{2.5}$.

As shown earlier, sources of $PM_{2.5}$ and window opening behaviours change considerably between the heating and non-heating seasons. Figure 26 illustrates the daily patterns of I/O $PM_{2.5}$ during the non-heating season, and Table 9 summarizes the corresponding I/O $PM_{2.5}$ data.

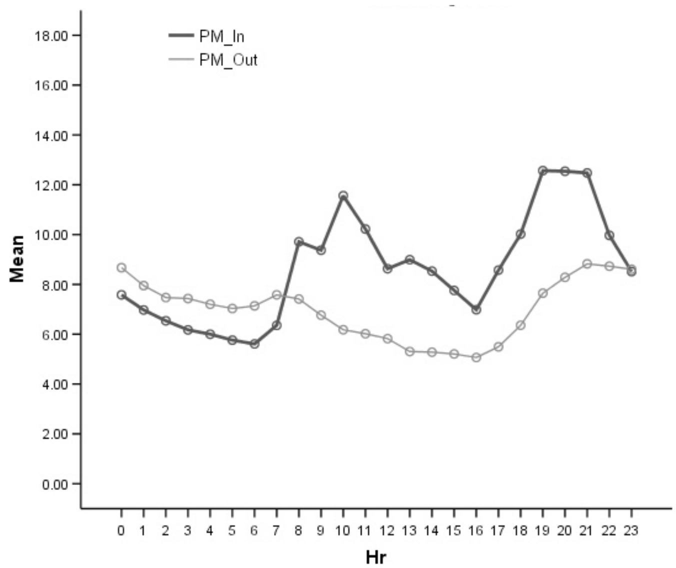

Figure 26. Diurnal pattern of I/O $PM_{2.5}$ during the non-heating season.

Table 9. Summary of I/O $PM_{2.5}$ during the non-heating season.

	Mean	**Med.**	**SD**	**10th**	**25th**	**75th**	**90th**
Night Indoor $PM_{2.5}$	5.22	4.46	4.20	1.51	2.63	6.92	9.43
Morning Indoor $PM_{2.5}$	8.00	4.77	17.64	1.76	2.98	7.40	11.95
Afternoon Indoor $PM_{2.5}$	6.77	4.67	11.89	1.81	3.11	7.02	10.71
Evening Indoor $PM_{2.5}$	8.92	5.89	17.79	2.36	3.81	8.90	13.74
Night Outdoor $PM_{2.5}$	7.61	6.58	5.27	2.41	3.95	9.94	14.32
Morning Outdoor $PM_{2.5}$	6.58	5.51	5.41	2.27	3.23	8.24	12.39
Afternoon Outdoor $PM_{2.5}$	5.34	4.68	4.11	2.05	3.06	6.90	9.46
Evening Outdoor $PM_{2.5}$	7.19	6.16	5.30	2.36	3.81	9.29	12.62
Night I/O Ratio	0.81	0.70	0.74	0.31	0.48	0.95	1.34
Morning I/O Ratio	1.54	0.91	4.12	0.37	0.56	1.33	2.05
Afternoon I/O Ratio	1.73	1.06	5.00	0.47	0.68	1.51	2.24
Evening I/O Ratio	1.63	1.04	2.92	0.42	0.66	1.47	2.47

Night (24:00-6:00); Morning (7:00-12:00); Afternoon (13:00-17:00); Evening (18:00-23:00)

Significant differences were found between I/O $PM_{2.5}$ ratios corresponding to different periods of the day. During the non-heating season the lowest I/O $PM_{2.5}$ ratio was 0.81, occurring from 23:00 to 6:00, and was significantly different ($p<0.00$) compared to the highest ratio that occurred during the afternoon (1.73) and evening (1.63). No significant differences in I/O $PM_{2.5}$ ratios existed for the morning, afternoon and evening periods.

Figure 27 illustrates the daily patterns of the I/O $PM_{2.5}$ during the heating season and Table 10 summarizes the corresponding I/O $PM_{2.5}$ data. During the heating season the lowest I/O $PM_{2.5}$ ratio was 0.96 and the highest 1.47. These two I/O $PM_{2.5}$ ratios were again significantly different (p=0.01). The highest mean $PM_{2.5}$ average occurred at 18:00 (13.07ug/m^3) when outdoor $PM_{2.5}$ was also highest (14.27ug/m^3).

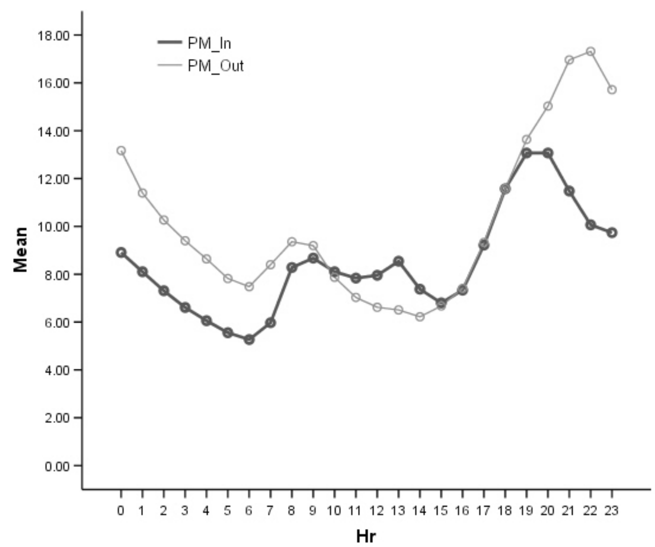

Figure 27. Diurnal pattern of I/O $PM_{2.5}$ during the heating season.

Table 10. Diurnal distribution of I/O $PM_{2.5}$ during the heating season.

	Mean	**Med.**	**SD**	**10th**	**25th**	**75th**	**90th**
Night Indoor $PM_{2.5}$	7.19	5.95	5.28	1.96	3.30	9.62	14.32
Morning Indoor $PM_{2.5}$	7.80	5.34	10.58	2.22	3.31	8.89	14.95
Afternoon Indoor $PM_{2.5}$	7.61	5.62	8.01	2.30	3.41	9.40	15.05
Evening Indoor $PM_{2.5}$	11.15	8.00	14.48	3.14	4.86	12.32	19.48
Night Outdoor $PM_{2.5}$	10.5	7.67	9.43	2.52	4.13	13.80	21.77
Morning Outdoor $PM_{2.5}$	8.07	5.94	6.29	2.65	3.85	10.20	16.32
Afternoon Outdoor $PM_{2.5}$	6.68	5.17	5.13	2.44	3.34	8.32	12.86
Evening Outdoor $PM_{2.5}$	14.3	10.4	12.0	3.86	5.96	18.74	29.83
Night I/O Ratio	0.96	0.71	0.89	0.29	0.48	1.07	1.89
Morning I/O Ratio	1.33	0.82	2.18	0.32	0.50	1.33	2.35
Afternoon I/O Ratio	1.47	0.95	1.90	0.44	0.65	1.61	2.79
Evening I/O Ratio	1.16	0.70	1.79	0.28	0.43	1.21	2.22

Night (24:00-6:00); Morning (7:00-12:00); Afternoon (13:00-17:00); Evening (18:00-23:00)

5.1.5 Indoor Activities and I/O $PM_{2.5}$

A large portion of the diurnal changes in residential $PM_{2.5}$ can be explained by the changing concentrations of ambient $PM_{2.5}$ in the CRD and meteorological conditions; however, residential behaviours also have a large impact on the relationship between I/O $PM_{2.5}$. During each monitoring event indoor behaviours were summarized using activity logs to examine the influence of indoor activities on residential I/O $PM_{2.5}$. To be included in the following analysis of indoor sources, occupants had to complete ninety percent of their activity log. Five monitoring events did not meet this criterion.

Table 11 summarizes the indoor activities that were recorded for 68 residential monitoring events. Activities are summarized as a percentage of the time that the monitors were operating in the home. This was determined by dividing the number of half hour increments that an activity was recorded by the total number of half hour increments during the monitoring event. For example, the mean time that cooking occurred during monitored residences was 5.7%, or 1.37 hours per day. It is important to note that activities recorded during monitoring are not one person's activities, but represent all the activities carried out in the residence. Activities are also not representative of the general population in the CRD as the sample of residences was not random.

Significant differences ($p<0.05$) were found between the heating and non-heating seasons only for windows opened and fireplace use. Cooking, cleaning, burning, HVAC use and residential occupancy did not significantly change between the two seasons.

Table 11. Summary of indoor residential activities (% time) during monitoring.

	Mean	Med.	SD	10^{th}	25^{th}	75^{th}	90^{th}
At Home							
Total	84.9	89.4	14.0	63.6	77.5	95.3	100.0
NH Season	85.7	88.7	11.6	68.8	78.7	94.1	97.9
H Season	84.1	90.0	16.2	59.6	73.6	96.7	100.0
Active							
Total	50.0	50.2	12.7	30.8	44.0	60.2	63.0
NH Season	51.7	49.9	9.3	40.1	45.9	60.8	64.1
H Season	48.1	53.4	15.3	23.6	36.1	60.1	62.3
Sleeping							
Total	35.0	35.8	5.8	29.6	32.5	38.1	40.9
NH Season	34.0	34.0	6.6	29.5	31.9	37.8	40.4
H Season	36.1	36.7	4.7	30.2	33.2	38.9	42.2
Cooking							
Total	5.7	4.9	3.6	1.6	3.1	7.4	10.6
NH Season	5.9	4.9	3.3	2.7	3.3	7.8	10.3
H Season	5.6	4.9	4.0	1.2	2.1	7.0	11.1
Window Open							
Total	29.6	8.8	35.5	0.0	0.4	50.5	97.5
NH Season	*46.6**	45.2	38.1	0.0	5.4	84.7	100.0
H Season	*12.0**	1.2	21.9	0.0	0.0	11.6	55.1
Cleaning							
Total	1.1	.8	1.3	0.0	0.0	1.6	2.9
NH Season	1.1	0.5	1.5	0.0	0.0	1.5	3.1
H Season	1.1	0.8	1.2	0.0	0.0	1.7	2.9
Burning[a]							
Total	0.2	0.0	0.6	0.0	0.0	1.6	2.9
NH Season	0.2	0.0	0.6	0.0	0.0	0.0	0.6
H Season	0.2	0.0	0.7	0.0	0.0	0.0	1.0
Fireplace							
Total	3.1	0.0	12.5	0.0	0.0	0.0	7.2
NH Season	*0.6**	0.0	1.8	0.0	0.0	0.0	3.7
H Season	*5.7**	0.0	17.5	0.0	0.0	2.1	18.7
HVAC							
Total	1.12	0.0	5.6	0.0	0.0	0.0	0.0
NH Season	0.9	0.0	5.0	0.0	0.0	0.0	0.0
H Season	1.6	0.0	6.8	0.0	0.0	0.0	0.0

[a] burning candles, incense. * Significant difference ($p<0.05$)

Household activities were examined against indoor $PM_{2.5}$ and I/O $PM_{2.5}$ ratios using cross-correlations. For the entire residential sample, percent time cooking and I/O $PM_{2.5}$ ratios were significantly correlated, and during the heating season percent time cooking and percent windows open were significantly correlated with I/O $PM_{2.5}$ ratios and mean indoor $PM_{2.5}$. No significant relationships were found in the non-heating season, which was expected as the relative contribution of indoor sources will decrease when air exchange rates are high (Hanninen et al. 2004). Table 12 summarizes the significant correlations between household activities and $PM_{2.5}$ monitoring data.

Table 12. Significant correlations between household activities and residential $PM_{2.5}$.

	Correlation	**Significance**
All		
% time cooking and I/O ratios	0.324	$p<0.000$
Heating Season		
% time cooking and I/O ratios	0.512	$p=0.002$
% time cooking and mean indoor $PM_{2.5}$	0.361	$p<0.000$
% window open and I/O ratios	0.348	$p=0.047$
% window open and indoor $PM_{2.5}$	0.352	$p=0.045$
Non-Heating Season		
N.A	-	-

There are no clear relationships between indoor activities and indoor $PM_{2.5}$ concentrations. While there are significant correlations between some indoor sources (shown in Table 12) the associations are limited to explaining only a small percentage of the variation within indoor $PM_{2.5}$ levels and between I/O $PM_{2.5}$. One potential hypothesis is that a number of variables may be interacting to hide the full effects of indoor sources. For example, Figure 28 illustrates the linear relationship, or lack thereof, between mean indoor $PM_{2.5}$ and percent time cooking during the entire year.

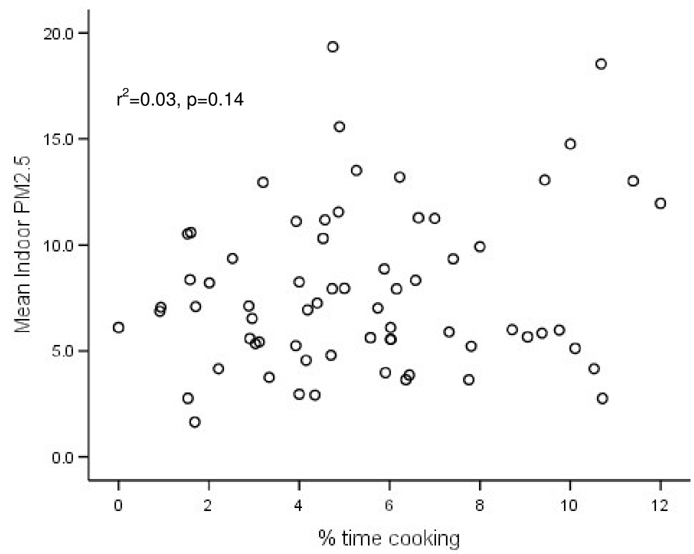

Figure 28. Mean indoor $PM_{2.5}$ and percent time spent cooking in the home.

A number of factors determine how much $PM_{2.5}$ is produced during cooking, while other factors determine how long the emitted $PM_{2.5}$ remains in the home. The use of an air exchange hood (i.e. fan) during cooking is an example of a major factor impacting the amount of $PM_{2.5}$ remaining in a house during and after cooking. Activity logs did not record this information, due to time constraints on participants; however, the household survey asked how often the range hood is used during cooking. The average use reported during cooking was between twenty five and fifty percent. Range hood use was correlated with percent time cooking (r=0.266, p=0.030) but not with indoor $PM_{2.5}$.

Residential air exchange is another factor that modifies the effect of indoor sources. The percent time cooking and mean indoor $PM_{2.5}$ levels during the heating season are shown in Figure 29, indicating a slight improvement in the relationship between these two variables over the non-heating season. One outlier was removed from analysis that had uncharacteristically high cooking times. During the summer, windows were open on average forty seven percent of the time, while in the winter they were open seventeen percent of the time. Reductions in air exchange rates during the winter resulted in indoor generated $PM_{2.5}$ remaining indoors for longer amounts of time.

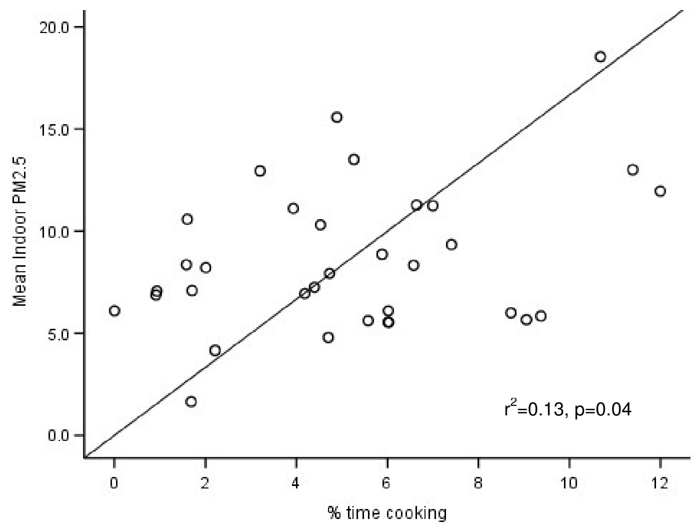

Figure 29. Indoor $PM_{2.5}$ and percent time cooking during the heating season.

The effect of opening and closing windows on residential $PM_{2.5}$ was examined by stratifying homes into those that had their windows open more than twenty percent of the time, and those that had their windows open less than twenty percent of the time. Twenty percent was selected as it stratifies air exchange rates into high and low categories and also includes enough households in each class for statistical analysis. Table 13 summarizes mean indoor concentrations for this stratification.

Table 13. Effect of window opening on residential indoor $PM_{2.5}$.

	Mean	Med.	SD	10th	25th	75th	90th
Windows open > 20%	7.2	5.9	4.2	2.9	3.8	9.6	11.9
Windows open < 20%	8.2	7.1	3.4	4.2	5.7	11.3	13.2

It appears that in the CRD having windows open provided a protective effect for indoor exposure to $PM_{2.5}$, specifically when indoor sources are present. Outdoor levels of $PM_{2.5}$ are relatively low in the CRD, and high air exchange rates diluted indoor generated $PM_{2.5}$. When outdoor $PM_{2.5}$ is higher than indoor $PM_{2.5}$ however higher air exchange rates will increase indoor $PM_{2.5}$.

5.1.6 Housing Characteristics and Residential Activities

No significant relationships were found between housing characteristics and residential activities. A stratification based on residential classes, such as detached homes and apartments and condominiums, was used to determine if significantly different activity patterns existed for different types of homes; however, no significant differences were found. It was hypothesized that household volume, represented by square footage, may be associated with different indoor source concentrations due to indoor sources of $PM_{2.5}$ being more concentrated in smaller homes while becoming more diluted in larger homes. The association with median indoor $PM_{2.5}$ was not significant ($r=-0.355$, $p=0.069$) but may indicate a potential relationship between volume and indoor $PM_{2.5}$, suggesting that smaller homes have higher indoor concentrations due to smaller air volumes to disperse indoor generated $PM_{2.5}$. Overall, the lack of association between residential activities and housing characteristics is not surprising, considering indoor activities generating $PM_{2.5}$ are typically independent of housing characteristics.

5.1.7 Socio-Economic Status (SES) and Residential $PM_{2.5}$

Different SES variables were collected in the residential surveys completed at the start of each monitoring event (survey shown in Appendix 4). The main goal of compiling SES variables was to examine the potential use of SPAD to represent SES; however, these variables also provided an opportunity to examine their associations with residential I/O $PM_{2.5}$.

Table 14 summarizes the results from cross-correlations of SES variables and indoor $PM_{2.5}$ for the yearly dataset and for monitoring events with windows open less than twenty percent of the time during monitoring (low air exchange residences). Categorized variables were correlated with mean indoor $PM_{2.5}$ using Kendall's tau-b correlation in SPSS.

Table 14. SES correlations to indoor $PM_{2.5}$.

	All Residences		**Low Air Exchange Residences**	
	Correlation	**Significance**	**Correlation**	**Significance**
# of Pets	0.07	0.55	0.01	0.94
# of Residents	0.12	0.31	0.32	*0.04**
Average Adult Age	0.05	0.67	0.02	0.89
# of Children	0.10	0.40	0.29	0.06
Occupation Class	0.06	0.62	0.12	0.45
Retired	0.06	0.62	-0.04	0.79
Gender	-0.07	0.61	-0.10	0.53
Ethnicity	-0.14	0.33	-0.25	0.10
Rental Price	0.02	0.96	0.09	0.85
Household Income	-0.03	0.82	-0.300	*0.05**

*Significant (p<0.05)

Significant correlations were found between the number of residents in a home and indoor $PM_{2.5}$ (r=0.32, p=0.04) and between household income and indoor $PM_{2.5}$ (r=-0.30, p=0.05) for low air exchange residences (windows open less than 20% of the time during monitoring). The correlations indicate that increased number of residents in a home leads to increased indoor $PM_{2.5}$ and that higher household income results in lower indoor $PM_{2.5}$ in low air exchange residences.

The relationships identified above correspond to the limited existing literature examining SES and residential air pollution. Table 15 provides a summary of large epidemiology studies that have examined SES factors as covariates in the analysis of particulate matter and health effects. The SES variables examined are those typically available for large populations and are therefore at a high level. Neighbourhood or housing SES factors have received little to no attention in large epidemiology studies.

Overall, the effects of SES on residential $PM_{2.5}$ exposure are not well understood. Jerrett el al. (2004) suggests that the limited number of studies examining SES as a confounder in health studies and the conflicting results of existing studies highlight the need for more research on the effects of SES factors and the different scales at which SES factors operate. The majority of existing research surrounding SES, $PM_{2.5}$ and health effects focuses on how lower SES tends to be associated with individuals being located in areas that have higher ambient air pollution (Gunier et al. 2003), are more likely to have greater occupational exposures (Rotko et al. 2000), have higher smoking prevalence (Watson et al. 2003) and have lower physical activity levels (Giles-Corti and Donovan 2002). No studies could be found that examined how SES affects the home environment itself and how this may modify indoor $PM_{2.5}$ exposure.

Table 15. Studies of particulate matter air pollution and SES (from O'Neill et al. 2003).

Reference	**Population**	**Pollutant**	**Health Outcome**	**SES Variables**	**Scale**	**Key findings**
HEI 2000	Harvard Six Cities Study	$PM_{2.5}$	Mortality	Education attainment	Individual/ person	Greatest effects among least educated
Pope et al. 2002	ACS (n=500,000)	$PM_{2.5}$	Mortality	Education attainment	Individual/ person	Greatest effects among least educated
Ito and Thurston 1996	Cook County, Illinois	PM_{10}	Daily Mortality	Race (black, white), sex	Individual/ person	Greatest effects among black women, then white women, black men, white men.
Gouveia and Fletcher 2000	Sao Paulo, Brazil	PM_{10}	Daily Mortality	Index of socio-economic conditions	Group/district	Effects larger in districts of higher SES levels.
Samet et al. 2000	20 U.S cities	PM_{10}	Daily Mortality	Education attainment, income, transportation	Group/county	No effect modification
Zanobetti and Schwartz 2000	Chicago, Detroit	PM_{10}	Daily Mortality	Race, sex, Education attainment	Individual/ person	Higher effect in women; race and educational attainment were weak modifiers
Cifuentes et al 1999	Santiago, Chile	$PM_{2.5}$	Daily Mortality	Education attainment	Individual/ person	Greatest effect among least educated
Wojtyniak et al. 2001	4 Polish cities	Black Smoke	Daily Mortality	Education attainment	Individual/ person	Greatest effect among least educated
Gwynn and Thurston 2001	New York	PM_{10}	Respiratory-cause hospital admissions	Race, insured and non-insured	Group/person	Higher effects among races other than white and uninsured
Zanobetti et al. 2000a	10 U.S cities	PM_{10}	Respiratory/ cardiovascular hospital admissions	% living in poverty, race	Individual/ person	No effects
Zanobetti et al. 2000b	Cook County, Illinois	PM_{10}	Respiratory/ cardio cause admissions	Race, sex	Group/zip code	No effects
Norris et al. 2000	Seattle, Washington	PM_{10}	Asthma, ED visits	High vs. low ED visit regions	Individual/ person	No effects
Linn et al. 2000	California	PM_{10}	Respiratory/ cardio cause admissions	Sex, ethnicity	Individual/pers on	Increased cardiovascular effects in blacks and whites relative to Hispanics
Tolbert et al. 2000	Atlanta, Georgia	PM_{10}	Asthma, ED visits	Race, Medicaid status, sex	Individual/ person	No effects

5.1.8 CRD Residential $PM_{2.5}$ Summary

Outdoor residential $PM_{2.5}$ was a poor predictor of total indoor residential $PM_{2.5}$ in the CRD. The five day r^2 between indoor and outdoor mean $PM_{2.5}$ was 0.31. Mean indoor and outdoor $PM_{2.5}$ levels were 7.9ug/m^3 and 8.45ug/m^3 respectively, and the average hourly I/O $PM_{2.5}$ ratio was 1.33ug/m^3 +/- 0.75. The 10th percentile of homes five days average indoor $PM_{2.5}$ was 5.30ug/m^3, while the 90th percentile of home indoor $PM_{2.5}$ was 13.14ug/m^3, highlighting the variations caused by indoor sources and infiltration between residences. Significant yearly and diurnal variations were also found in residential indoor $PM_{2.5}$ and in the I/O $PM_{2.5}$ ratios.

Indoor $PM_{2.5}$ sources had extremely variable influences on indoor residential $PM_{2.5}$, suggesting that to predict total indoor $PM_{2.5}$ detailed information is required for each source activity. For example, to determine how much indoor $PM_{2.5}$ is generated from cooking, the type of stove, exhaust fan use, cooking temperature, and type of food being prepared needs to be considered. These types of studies are best undertaken in a controlled setting; for example, Brauer et al. (2000) examined indoor cooking and found an average output of $PM_{2.5}$ from a low of 1.5+/-0.6 mg/min to a high of 4.9+/-1.3mg/min. The problems associated with predicting indoor generated $PM_{2.5}$ is that certain indoor activities that generate $PM_{2.5}$ are highly random. Diurnals patterns do exist corresponding to when people typically cook; however, predicting the levels of $PM_{2.5}$ created from these activities requires very detailed information for which data are not available.

Predicting ambient $PM_{2.5}$ inside residences does not require the prediction of indoor sources. A number of studies have concluded that it is the ambient component of

$PM_{2.5}$ that is causing health effects and that ambient and indoor generated $PM_{2.5}$ are distinct pollutants that need to be separated for examination in epidemiology studies (Elgert 2004). To separate indoor $PM_{2.5}$ into its indoor generated and ambient components, infiltration must be determined.

The following section presents calculated residential infiltration factors for the CRD and Seattle samples and examines the potential for modeling infiltration to determine indoor ambient $PM_{2.5}$ using meteorological conditions and housing characteristics from SPAD.

5.2 Modeling Residential $PM_{2.5}$ Infiltration

Infiltration is defined as the equilibrium fraction of air pollution that penetrates indoors and remains suspended (Wallace 1996). The benefit of using an infiltration factor in place of I/O ratios is that infiltration can be calculated for occupied homes by censoring out indoor sources. Infiltration therefore allows for the stratification of indoor $PM_{2.5}$ into its indoor ambient and indoor generated components under occupied conditions. Infiltration also incorporates important information on the penetration and decay of $PM_{2.5}$, which are important as Bennet and Koutrakis (2006) found that I/O ratios often overestimate penetration efficiency. Infiltration values were calculated for each monitored residence in the CRD and Seattle using the recursive mass balance equation shown in Chapter 4.2.

5.2.1 CRD Residential $PM_{2.5}$ Infiltration

The quality control criteria applied to the 73 monitoring events in the CRD resulted in the removal of twelve events, leaving 61 monitoring events suitable for calculating infiltration. The criteria required that the I/O data have a significant ($p<0.05$)

relationship during non-source periods (23:00-6:00) and that the median I/O ratio during non-source periods was less than or equal to one (Summary data shown in Appendix 6). These criteria were developed by the Seattle study (Allen et al. 2003) and ensured that the infiltration factors calculated represented ambient $PM_{2.5.}$

The mean infiltration factor calculated from the 61 monitoring events in the CRD was 0.59 +/-0.22. The minimum infiltration value was 0.21 and the maximum infiltration was 1.00. Figure 30 shows that infiltration factors were normally distributed. A significant difference was found between infiltration in the heating and non-heating seasons. Table 16 summarizes all infiltration factors in the CRD and includes a stratification based on the heating and non-heating seasons. Appendix 7 also provides summary statistics for each of the 61 infiltration values

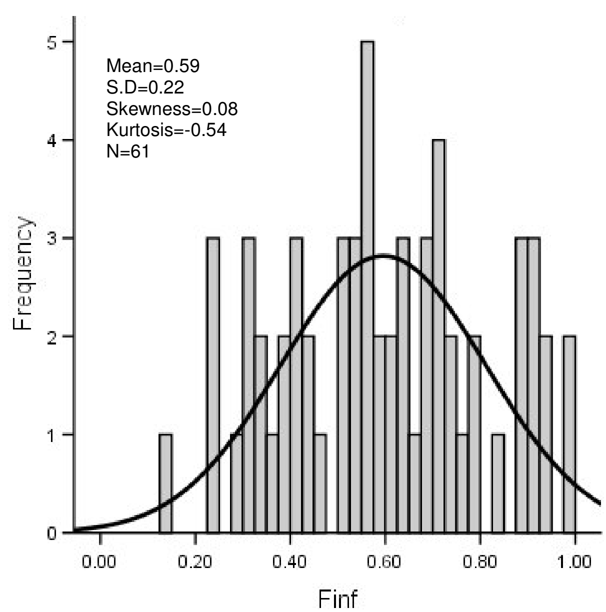

Figure 30. Distribution of residential infiltration in the CRD sample.

Table 16. Seasonal differences in residential infiltration in the CRD.

Infiltration	Mean	Med.	SD	Min	Max	10th	25th	75th	90th
All	0.59	0.57	0.22	0.15	1.00	0.30	0.46	0.71	0.91
HS	0.48	0.48	0.16	0.15	0.86	0.28	0.33	0.57	0.70
NHS	0.69	0.70	0.19	0.22	1.00	0.43	0.57	0.85	0.97

The spatial distribution of infiltration factors for the heating and non-heating seasons are provided in Figures 31 and 32. No spatial clustering was identified using the local Morans I statistic for both the heating season (Z=0.15) and non-heating season (Z=0.14).

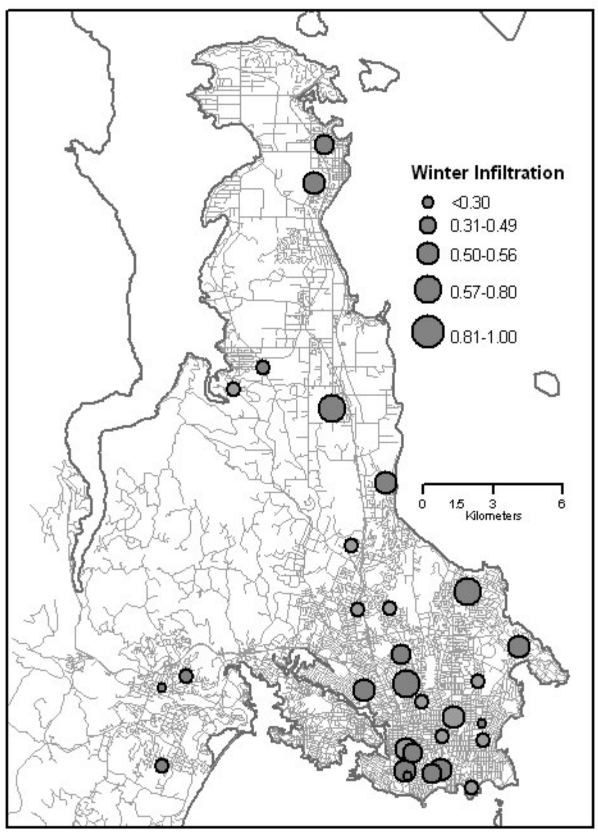

Figure 31. Spatial distribution of residential infiltration in the heating season.

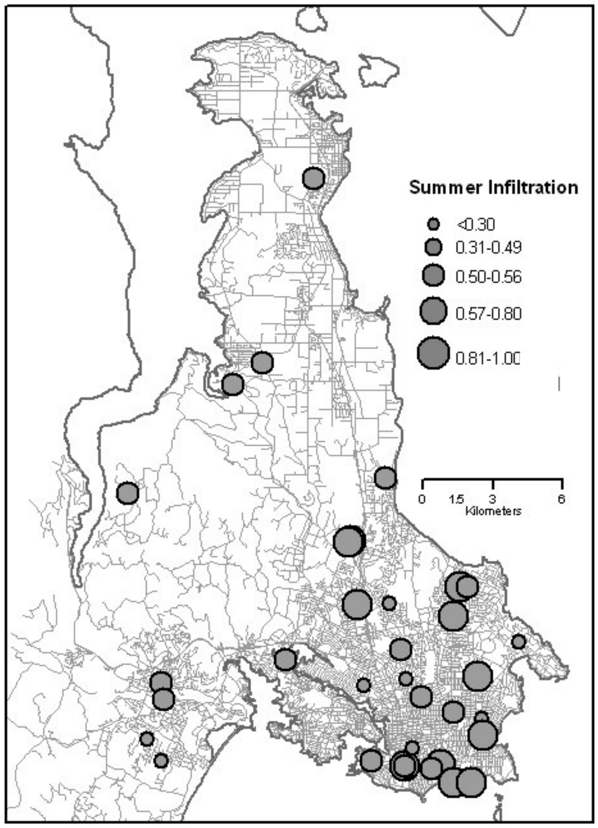

Figure 32. Spatial distribution of residential infiltration in the non-heating season.

A wide range of residential infiltration factors were found between homes and between monitoring events for the same home, reflecting the variable nature of residential infiltration. Seasonality, environmental variables, indoor behaviours, and housing characteristics may all be influencing the amount of ambient $PM_{2.5}$ within a residence and hence be producing the large $PM_{2.5}$ infiltration differences found in the CRD. These factors will be examined in the overall infiltration sample from the CRD and Seattle; however, the indoor activity logs and occupant questionnaires completed for the CRD sample are not available for the Seattle monitoring data. Therefore, the affects of indoor activities and SES influences on infiltration will first be examined for the CRD residential sample only.

5.2.1.1 Indoor Activities and Residential $PM_{2.5}$ Infiltration

Data collected from the CRD time-activity logs provide detailed information to examine the influences of indoor activities on residential infiltration and to evaluate the censoring protocol used to remove indoor sources.

Indoor activities other than window opening behaviour should not be associated with infiltration as the censoring protocol described earlier was intended to remove all indoor sources. Table 17 summarizes the correlations between indoor activities and infiltration. Infiltration was not significantly correlated with any indoor activities, except window opening behaviour, which indicates that the censoring methods applied to the indoor $PM_{2.5}$ data correctly censored indoor sources.

Table 17. Correlation results between residential activities and infiltration

Household Activities	**Correlation**	**Sig.**
% time home occupied	-0.001	0.993
% time active in home	0.018	0.892
% time sleeping	-0.041	0.762
% time cooking	0.149	0.272
% time windows open	0.383	*0.004**
% time cleaning	0.059	0.668
% indoor burning	0.068	0.620
% fireplace use	-0.138	0.310
% filter use	0.002	0.989

Figure 33 illustrates the relationship between the percent time windows were open during monitoring and infiltration (r^2=0.147, p=0.004). Infiltration will increase as more windows are open in a home and as air exchange increases. It seems however that more information is needed on the location, width, and number of windows open in a home to determine the exact effect on air exchange, and in turn infiltration.

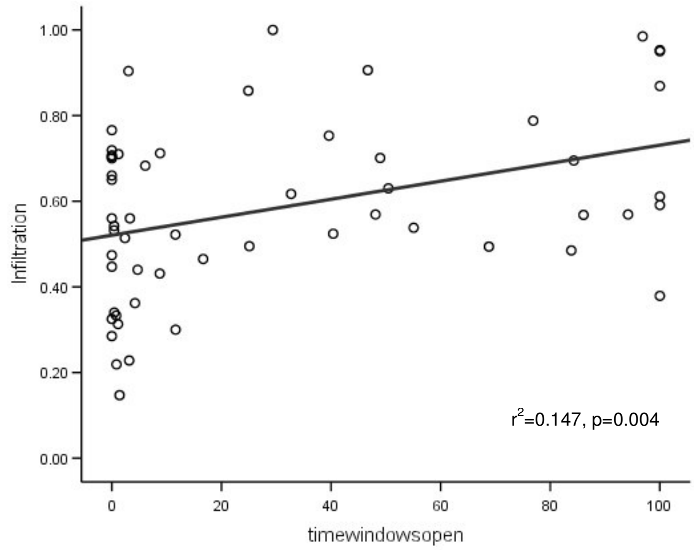

Figure 33. Infiltration and percent time windows open during monitoring.

The width of windows open in a home during monitoring was recorded in the activity logs and a function (% time windows open multiplied by average width) was used to examine if window opening widths could improve the relationship shown in Figure 33. The resulting relationships (r^2=0.115, p=0.013) indicates that incorporating widths does not improve the relationship between windows open and infiltration. This may be due to a number of factors, such as aggregating data over the five days monitoring period, different locations and numbers of windows open, or improperly completed activity logs. From my experience collecting activity logs after each monitoring event, it is reasonable to assume that the accuracy of each log will vary greatly.

5.2.1.2 Socio-Economic Variables and Residential $PM_{2.5}$ Infiltration

Caution must be taken when interpreting the effects of SES variables on residential infiltration due to the small sample size. The relationship between SES and housing characteristics however may provide information on the influence of SES on infiltration due to infiltration being influenced directly by housing characteristics.

No significant correlations were found between SES and infiltration. Correlations were examined during different seasons and for different building types (detached, apartments, condominiums). SES variables included number of residents, age, number of children, occupational class, retired status, gender, ethnicity, rental and rental price, and household income.

A number of SES variables were correlated with detached residential building characteristics from SPAD. Average adult age was significantly correlated to residential square footage (r=0.405, p=0.005), total value of the residence (r=0.529, p=0.000) and improved value of the residence (r=0.302, p=0.058). Household income was correlated with number of pets (r=0.273, p=0.063), number of rooms (r=0.581, p=0.000), square footage (r=0.600, p=0.000), and residential improved value (r=0.400, p=0.011) and total value (r=0.392, p=0.012).

5.2.1.3 SPAD Sensitivity Analysis

Residential surveys were conducted primarily to examine the accuracy of SPAD to represent building characteristics. This analysis examines how well SPAD corresponds to data collected for each of the 73 monitored residences. Table 18 summarizes the correlations between residential characteristics collected in residential surveys and housing characteristics reported by SPAD. Household characteristics that do not change, such as building age, were highly correlated while residential characteristics that are easily modified, such as improved age, were only slightly correlated.

Table 18. Correlations between household characteristics collected in the residential survey and SPAD.

Household characteristics	Correlation	Sig.
Age of home	0.997	*0.000**
Improved age	0.345	*0.034**
Square footage	0.852	*0.000**
# of bedrooms	0.410	*0.011**
Fireplace	0.374	*0.021**
Heating type	0.545	*0.000**

The lack of association between some variables may also be a result of individual reporting. For example, the low correlation for fireplaces may be due to residences reporting using a fireplace rather than presence of a fireplace. This however provided useful information that suggests the presence of a fireplace may not be a strong predictor of fireplace use (r=0.374). Figures 34 and 35 illustrate an example of SPAD as an accurate data source for such variables as year built and square footage.

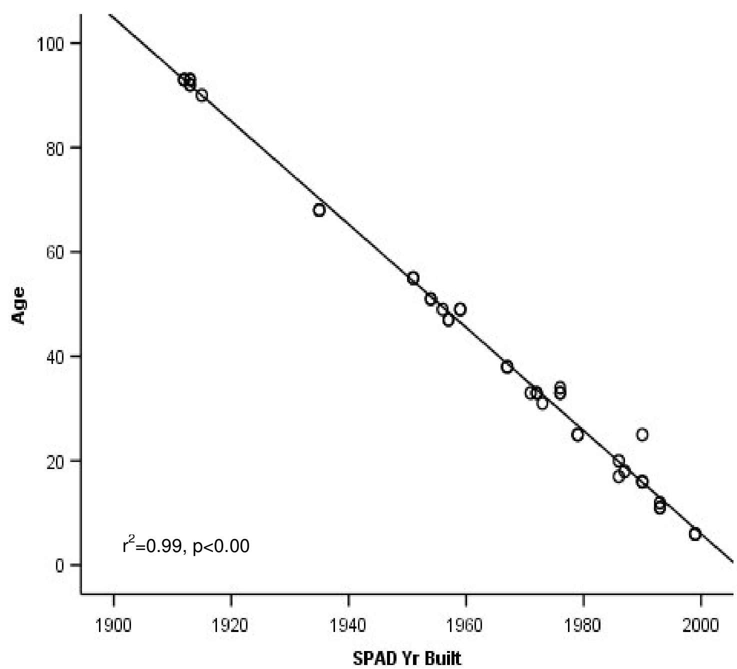

Figure 34. Relationship between SPAD year built and reported building age.

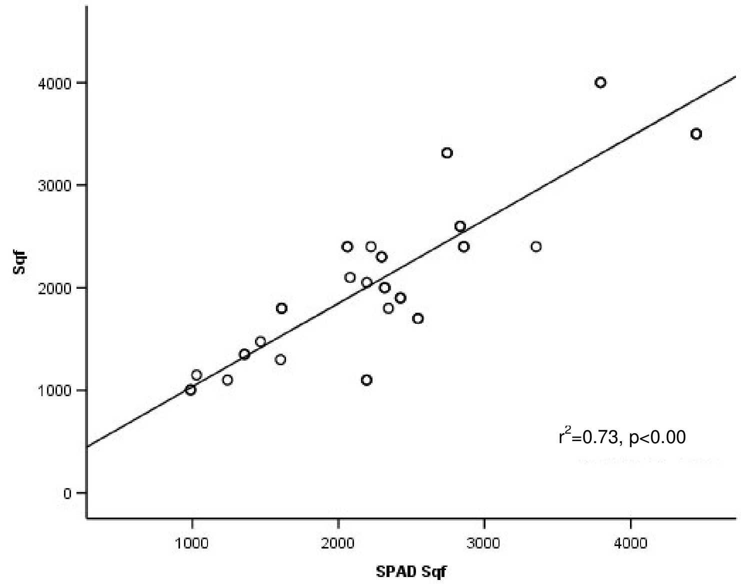

Figure 35. Relationship between SPAD and reported square footage.

5.2.2 Seattle $PM_{2.5}$ Infiltration Summary

Existing I/O $PM_{2.5}$ data were compiled from a previous study conducted in Seattle Washington for 44 unique residences and 61 monitoring events (each house may have been monitored more than twice) (Liu et al. 2003). Infiltration was recalculated using the methodology applied to the CRD residential sample to ensure consistency between the two data sets.

The mean infiltration factor calculated from the Seattle sample was 0.62 +/-0.21. The minimum infiltration value was 0.23 and the maximum infiltration value was 1.00. Figure 36 illustrates the distribution of Seattle infiltration and Table 19 provides summary infiltration statistics, as well as statistics for the heating and non-heating seasons. Similar to the CRD, no spatial clustering of infiltration values were present in the Seattle sample (Local Moran's I Z=0.24).

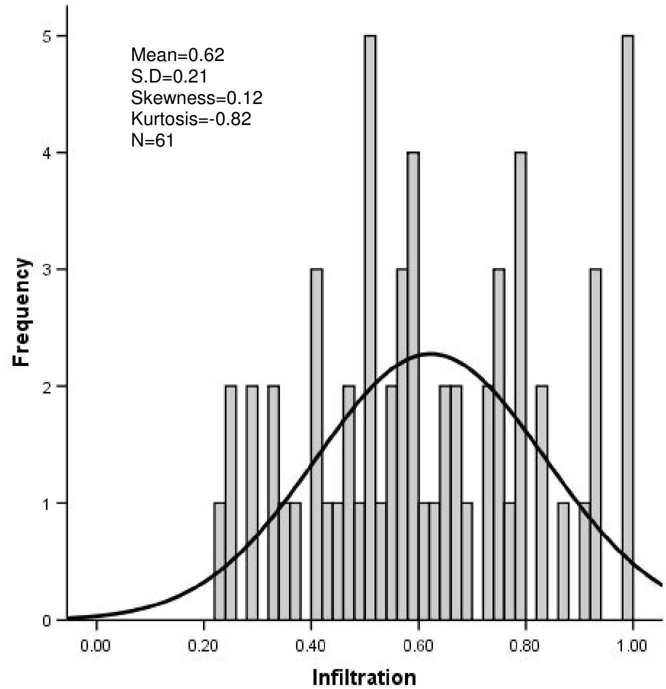

Figure 36. Distribution of Seattle residential infiltration.

Table 19. Summary of infiltration for Seattle residences.

Infiltration	Mean	Med.	SD	Min	Max	10th	25th	75th	90th
All	0.62	0.59	0.21	0.23	1.00	0.34	0.47	0.79	0.93
HS	0.50	0.51	0.15	0.23	0.91	0.30	0.40	0.59	0.66
NHS	0.79	0.79	0.18	0.24	1.00	0.56	0.72	0.93	1.00

Collecting residential $PM_{2.5}$ infiltration data is expensive and time-consuming. The opportunity to combine the CRD and Seattle infiltration samples to examine infiltration is opportune, since both studies used the same monitoring methodologies and the two residential samples are similar in geography, climate and housing characteristics.

5.2.3 Combining CRD and Seattle Residential Infiltration Samples

A chow-test (determines whether the coefficients in a regression model are the same in separate samples) and linear regression approach with infiltration as the dependent and a dummy variable (either CRD or Seattle) as the independent were used to examine whether the two infiltration samples could be combined to further explore residential infiltration. Both the chow-test and regression approach indicated that Seattle and CRD data were not significantly different (chow-test $f_{critical}<f_{value}$, regression dummy variable p=0.30). Table 20 also provides summary I/O $PM_{2.5}$ and infiltration statistics from each sample. The combined sample distribution (Figure 37) is normally distributed and similar to both the CRD and Seattle dependent samples.

Table 20. I/O $PM_{2.5}$ and infiltration summary for Seattle and the CRD.

	Mean	**Med.**	**SD**	**10th**	**25th**	**75th**	**90th**
CRD Outdoor $PM_{2.5}$	8.78	8.51	3.91	4.26	5.71	11.44	13.81
Seattle Outdoor $PM_{2.5}$	10.21	9.72	3.91	4.24	5.60	11.90	13.91
CRD Indoor $PM_{2.5}$	7.26	6.53	3.27	3.33	5.17	8.85	11.50
Seattle Indoor $PM_{2.5}$	8.15	8.04	2.25	5.64	6.75	9.65	10.60
CRD Infiltration	0.59	0.57	0.21	0.30	0.45	0.71	0.90
Seattle Infiltration	0.62	0.59	0.22	0.34	0.47	0.79	0.93

Residential infiltration for both the CRD (0.59) and Seattle (0.62) are similar, have mean infiltration factors within 0.03, and are not significantly different (p=0.69). The following analysis of residential $PM_{2.5}$ infiltration, seasonality, meteorological conditions and housing characteristics will therefore be conducted on the combined CRD and Seattle sample of 122 monitoring events.

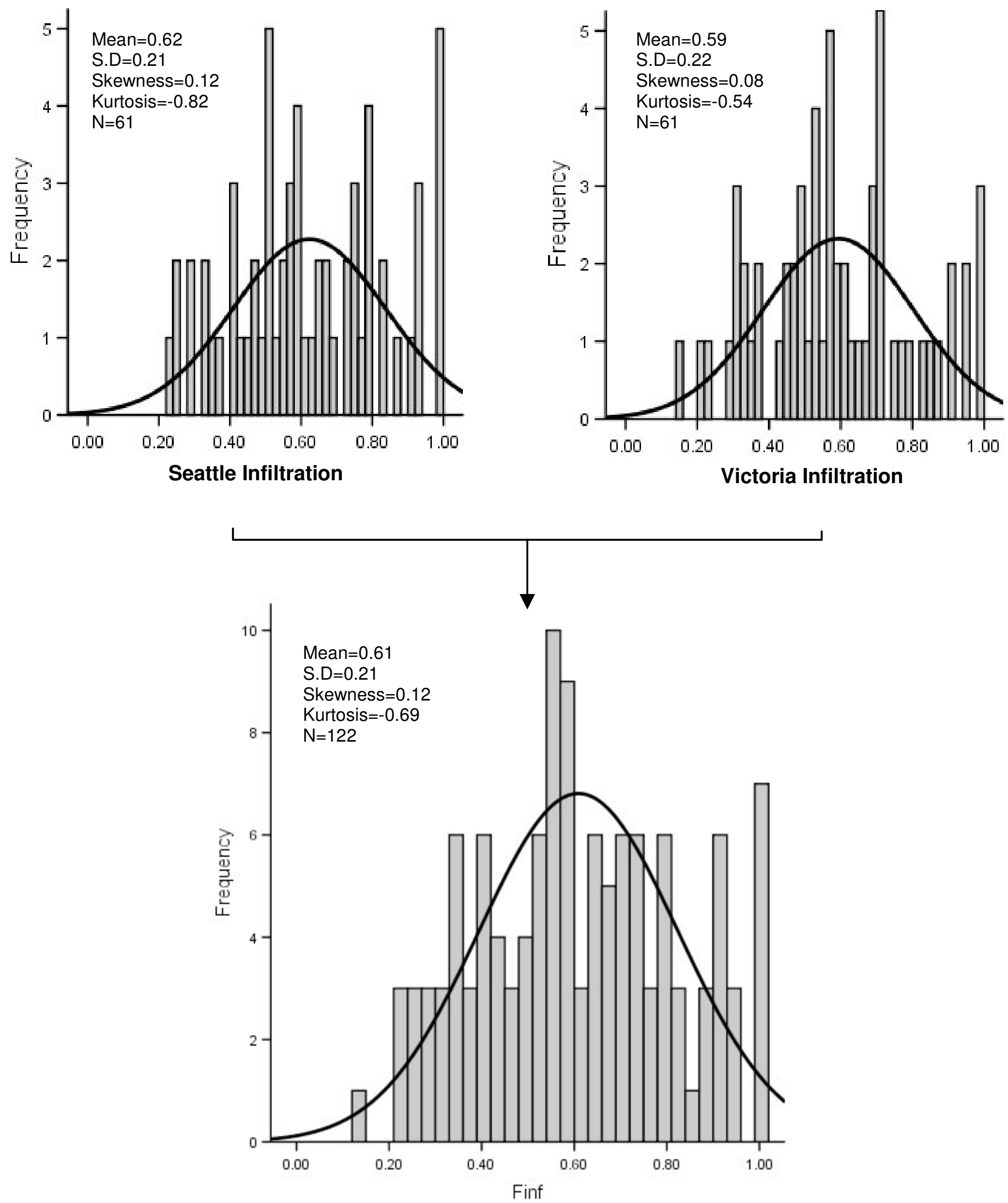

Figure 37. Distribution of combined CRD and Seattle residential infiltration sample.

5.2.3.1 Seasonal Variations of Residential $PM_{2.5}$ Infiltration

Monitoring occurred throughout the year for both Seattle and CRD residences allowing for the analysis of seasonal patterns of residential $PM_{2.5}$ infiltration. Figure 38 illustrates mean monthly infiltration levels and 95% confidence intervals. Large confidence intervals for July and November resulted from small sample sizes (n=5) during these two months.

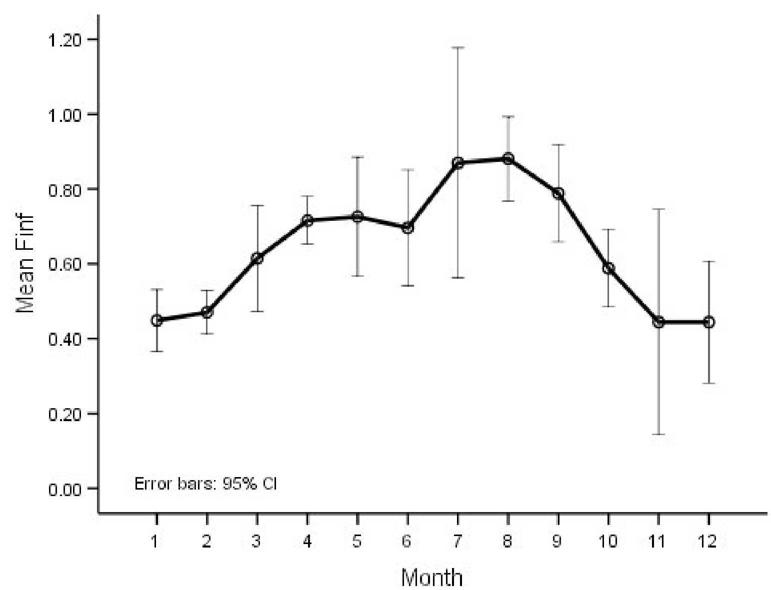

Figure 38. Monthly residential $PM_{2.5}$ infiltration for Seattle and the CRD (where 1=Jan., 2=Feb., etc.).

Quadratic regression analysis was also used to examine ‘month’ as a predictor of residential $PM_{2.5}$ infiltration. The combined sample resulted in month explaining 35 percent of the variation in infiltration ($p<0.00$). Figure 39 illustrates the quadratic for Seattle, CRD, and combined infiltration sample.

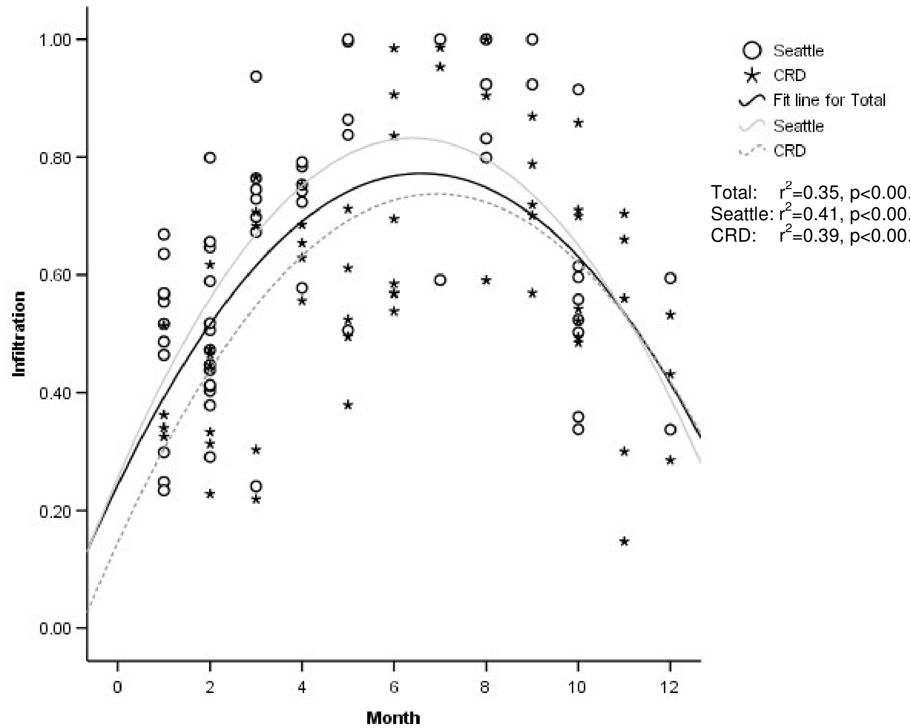

Figure 39. Quadratic equation between month and infiltration (where 1=Jan., 2=Feb., etc.).

Monthly infiltration factors clearly indicate distinct seasonal variations, with infiltration decreasing in winter months and increasing in summer months. A heating season and non-heating season stratification was used to examine the general changes in infiltration caused by seasonality. Table 21 summarizes yearly and heating and non-heating season infiltration statistics. Mean infiltration during the heating season was 0.49 and during the non-heating season 0.72. In the non heating season infiltration was slightly higher in Seattle (0.79) than in the CRD (0.69), which is most likely due to sample characteristics. Overall, heating season as a dummy variable explained 36 percent of infiltration variation ($p<0.00$).

Table 21. Yearly, heating and non-heating season infiltration.

	Mean	Med.	SD	Min	Max	10^{th}	25^{th}	75^{th}	90^{th}
Yearly									
Total	0.61	0.59	0.21	0.15	1.00	0.32	0.46	0.75	0.92
CRD	0.59	0.57	0.21	0.30	0.45	0.30	0.46	0.71	0.91
Seattle	0.62	0.59	0.21	0.23	1.00	0.34	0.47	0.79	0.93
HS									
Total	0.49	0.49	0.15	0.15	0.91	0.29	0.36	0.59	0.69
CRD	0.48	0.48	0.16	0.15	0.86	0.28	0.33	0.57	0.70
Seattle	0.50	0.51	0.15	0.23	0.91	0.30	0.40	0.59	0.66
NHS									
Total	0.72	0.74	0.19	0.22	1.00	0.50	0.59	0.88	1.00
CRD	0.69	0.69	0.19	0.22	1.00	0.41	0.57	0.82	0.98
Seattle	0.79	0.79	0.18	0.24	1.00	0.56	0.72	0.93	1.00

5.2.3.2 Meteorological Conditions and $PM_{2.5}$ Infiltration

Seasonal variations in residential $PM_{2.5}$ infiltration are likely the outcome of changing air exchange rates resulting from different meteorological conditions and window opening behaviours. Simply, during warmer weather people are more likely to have their windows open, while in colder weather people tend to have their windows closed. Figure 40 shows the significant relationship between temperature and infiltration (r^2=0.39, p<0.00) and Figure 41 illustrates similar patterns between infiltration and relative humidity (r^2=0.05, p=0.01). Precipitation data was available only for the CRD, which was significantly related to infiltration (r^2=0.07, p=0.04). No significant relationship was found between infiltration and wind speed (r^2=0.002, p=0.66). Table 22 summarizes the regression coefficients for each meteorological variable examined.

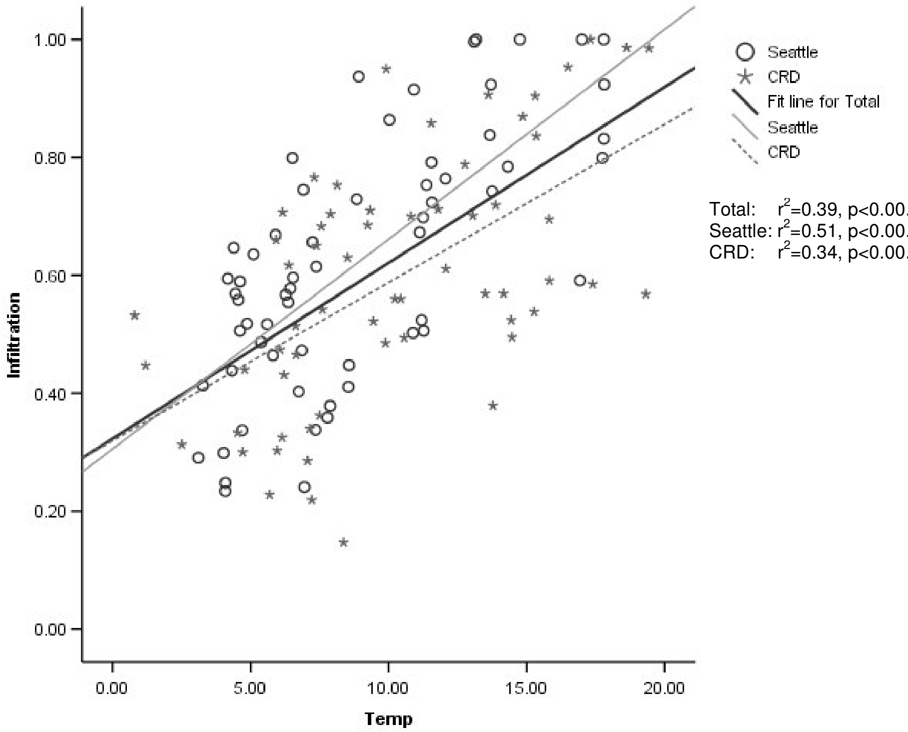

Figure 40. Residential $PM_{2.5}$ infiltration and Temperature.

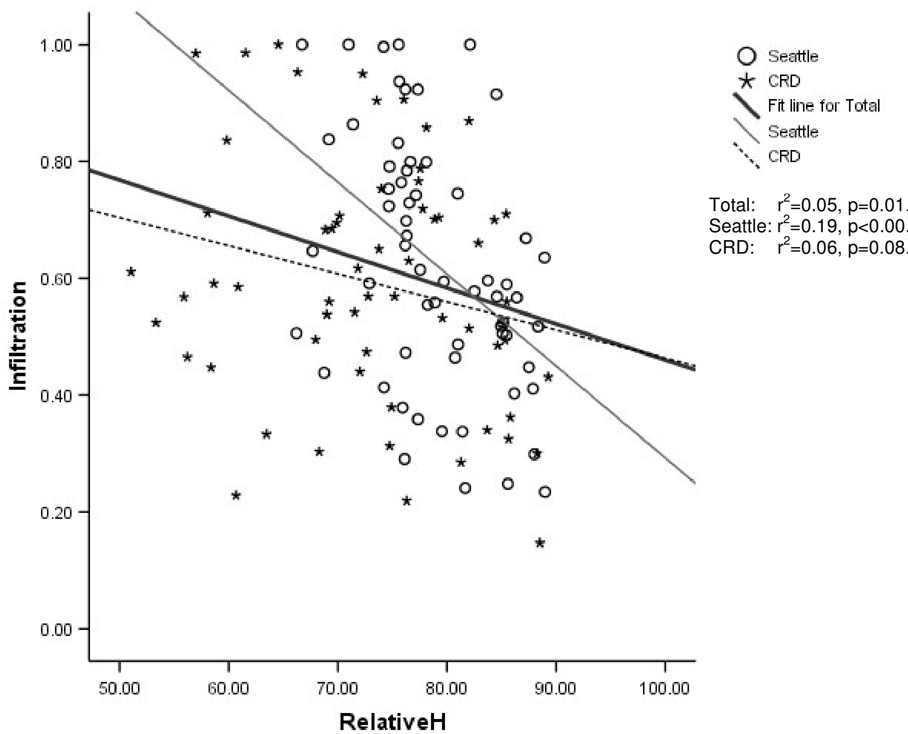

Figure 41. Residential $PM_{2.5}$ infiltration and Relative humidity.

Table 22. Regression coefficients for infiltration and meteorological variables.

Variable	Constant	Ceof.	r^2	p	n
Temperature (°C)					
All	0.323	0.030	0.387	0.000*	122
Seattle	0.306	0.036	0.506	0.000*	61
Victoria	0.320	0.027	0.338	0.000*	61
Relative Humidity (%)					
All	1.076	-0.006	0.064	0.005*	122
Seattle	1.866	-0.016	0.189	0.000*	61
Victoria	0.945	-0.005	0.052	0.077	61
Wind Speed (m/s)					
All	0.623	-0.008	0.002	0.659	122
Seattle	0.869	-0.082	0.053	0.074	61
Victoria	0.621	-0.019	0.005	0.598	61
Precipitation (mm)					
All	0.622	-0.003	0.073	0.035*	61
Seattle	-	-	-	-	-
Victoria	0.622	-0.003	0.073	0.035*	61

* Significant ($p<0.05$).

Recorded average wind speeds for Seattle residences were consistently higher than wind speeds recorded in the CRD during monitoring. This may be due to higher average wind speeds in Seattle during the time of monitoring, the location of meteorological stations, or measurement error. A fine resolution meteorological network was used in the CRD to capture local meteorological conditions, while in Seattle one central meteorological station was used. Analysing the two samples separately did not reveal significant relationships between wind speeds and infiltration (CRD p=0.506, Seattle p=0.074), indicating that wind speed is not a strong determinant of residential infiltration.

5.2.3.3 Residential Type and $PM_{2.5}$ Infiltration

Initial analysis of the Seattle infiltration sample revealed that there may be differences between housing types, classed as detached (mean infiltration = 0.60), apartments/ condominiums (0.70) and group homes (0.51). The combined sample however did not result in a significant difference between residential classes. Figure 42 illustrates the distribution of infiltration for each housing class for the combined sample, showing the median, 25th and 75th percentiles and minimum and maximum infiltration values. The 'other' residential class incorporates row houses, townhouses and group homes.

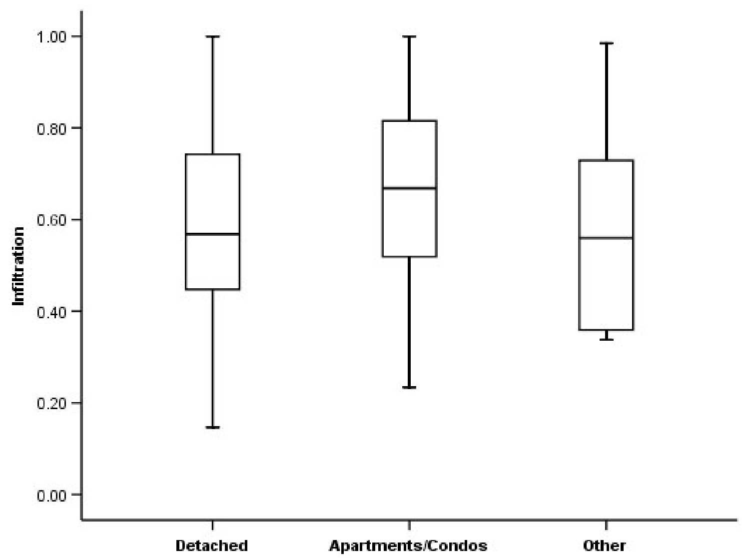

Figure 42. Infiltration factors for different residential classes.

Small differences in average infiltration were found between residential classes (not significant) that correspond to the initial Seattle analysis. Apartments and condominiums continued to have the highest average infiltration (0.64) followed by detached homes (0.59) and other residences (0.55). No significant differences existed between residential classes: detached homes and apartments/condominiums (p=0.63); detached homes and other residences (p=0.34); and apartments/condominiums and other residences (p=0.27).

The application of SPAD to residences other than detached homes is limited due to the type and format of data collected in BC and in Snohomish County. Information on apartments, condominiums, and townhouses was limited to providing information for the whole building and did not provide detailed information on each unit. King County however collected SPAD that provided information on individual units, similar to information collect for detached residences. Due to the lack of SPAD for residences other than detached homes, the following analysis focuses on predicting infiltration for detached residences only.

5.2.3.4 SPAD Building Characteristics and Detached $PM_{2.5}$ Infiltration

A number of detached housing characteristics were correlated with $PM_{2.5}$ infiltration. Table 23 summarizes the correlation between housing characteristics available in SPAD and detached residential $PM_{2.5}$ infiltration. Categorized variables were correlated with infiltration using Kendall's tau-b correlation in SPSS. A number of variables were coded into categories to represent distinct conditions that may affect infiltration. For example, building codes changed around 1980 in both Seattle and Victoria to require homes to be more energy efficient and tighter (lower air exchange rates) due to rising energy costs. During the heating season, infiltration is not overpowered by opening windows and therefore additional factors, such as housing characteristics, can be further examined for their affects on infiltration.

Table 23. Correlations between detached infiltration and SPAD characteristics (n=84).

	Description	Correlation	Significance
Age	(Interval)		
All		0.001	0.994
HS		0.261	0.087**
NHS		-0.097	0.551
Age Improved	(Interval)		
All		-0.054	0.624
HS		0.058	0.710
NHS		0.004	0.983
# of Stories	(Ordinal)		
All	1, 1.5, 2, 3	-0.001	0.902
HS	1, 1.5, 2, 3	0.108	0.393
NHS	1, 1.5, 2, 3	-0.072	0.588
# of Bedrooms	(Ordinal)		
All	1, 2, 3, 4, 5	0.029	0.791
HS	1, 2, 3, 4, 5	0.071	0.646
NHS	1, 2, 3, 4, 5	0.067	0.681
Heating Source	(Nominal)		
All	0=other (oil/gas), 1=electric	-0.061	0.583
HS	0=other (oil/gas), 1=electric	-0.261	0.087**
NHS	0=other (oil/gas), 1=electric	0.082	0.613
Fireplace	(Nominal)		
All	0=no, 1=yes	-0.071	0.519
HS	0=no, 1=yes	-0.043	0.792
NHS	0=no, 1=yes	-0.118	0.447
Square Footage	(Interval <3000)		
All		-0.085	0.477
HS		-0.313	0.056**
NHS		-0.050	0.778
Improved Value	(Interval)		
All		0.051	0.660
HS		-0.309	*0.050**
NHS		0.142	0.403
Total Value	(Interval)		
All		0.051	0.660
HS		-0.268	0.095**
NHS		0.096	0.572
Condition	(Nominal)		
All	1=Good, 0=less than good	-0.076	0.199
HS	1=Good, 0=less than good	-0.325	*0.041**
NHS	1=Good, 0=less than good	0.302	0.174

* Significant ($p<0.05$) ** May indicate trend

Figure 43 illustrates the relationship between age and infiltration during the heating season and Figure 44 illustrates the relationship between categorized age and infiltration during the heating season.

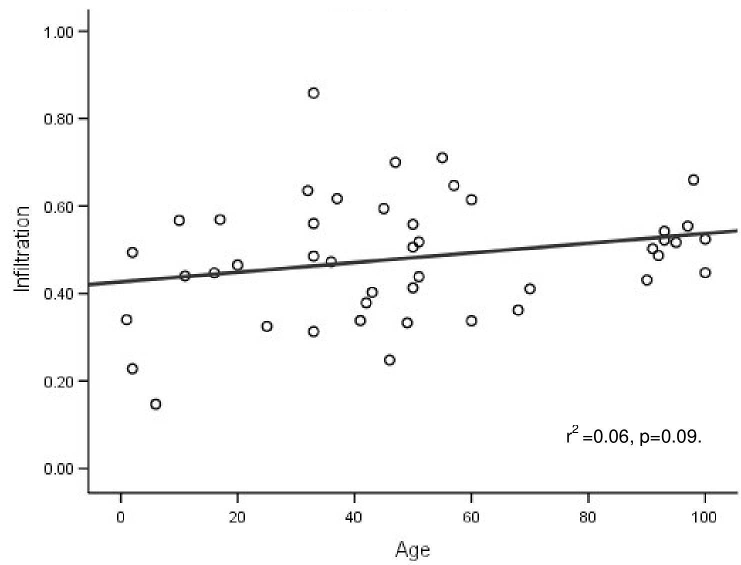

Figure 43. Infiltration and detached residential age during the heating season.

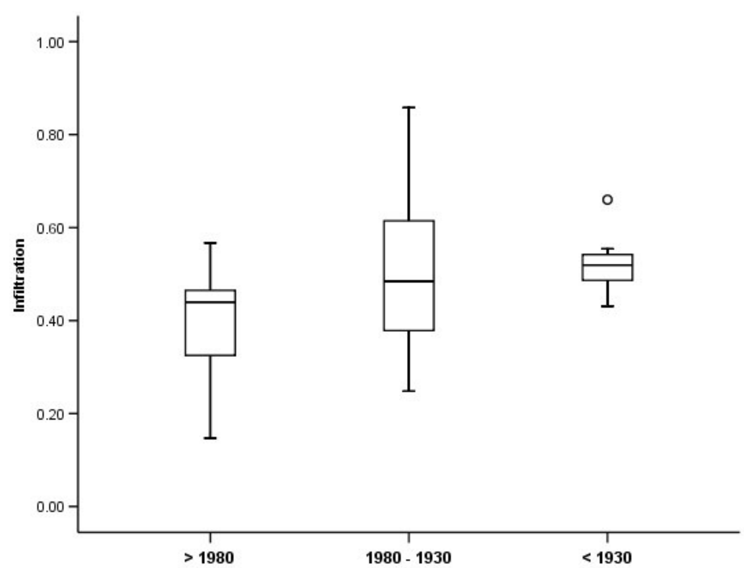

Figure 44. Infiltration and detached categorized residential age during the heating season.

A number of housing characteristics were not significantly (p<0.05) correlated with infiltration, yet a number of associations may exist. Analysis of residential heating and infiltration found that homes heated by oil or gas (forced hot air heating) had higher infiltration factors than home heating by electric sources (r=0.261, p=0.087). Square footage of detached residences during the heating season was also associated with infiltration (r=-0.313, p=0.056). Figure 45 illustrates the relationship between square footage and infiltration during the heating season. Three outliers were removed (>3000 square feet).

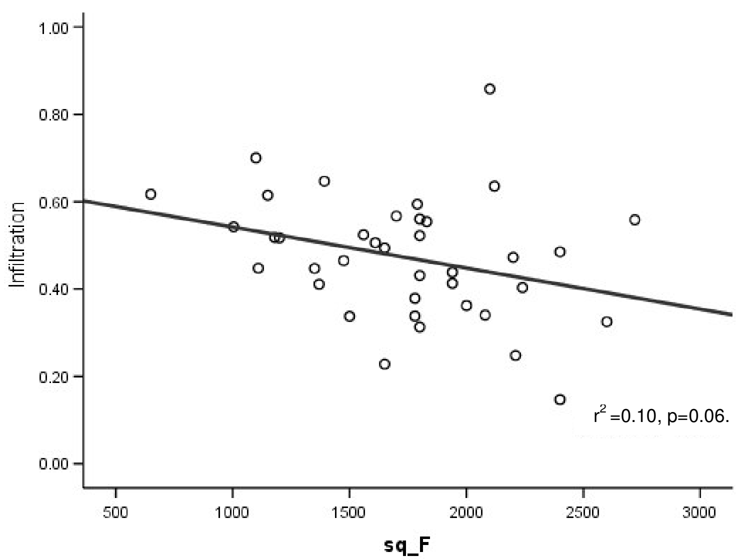

Figure 45. Detached residential square footage (<3000) and infiltration during the heating season.

A large range of residential improved values was found for the combined sample, ranging from 50,000 to 566,000. Improved values were therefore classed into <150,000, 150,000 to 250,000, and > 250,000 to represent general housing conditions and building quality. Seattle residential values were converted to Canadian dollars using an exchange rate of 0.81. Figure 46 illustrates the relationship between the three improved value classes and detached residential infiltration during the heating season. The relationship between improved detached residential value and infiltration indicates that as improved values increase, infiltration decreases. Residences with the lowest improved values had infiltration factors significantly larger than higher improved value homes (p=0.02).

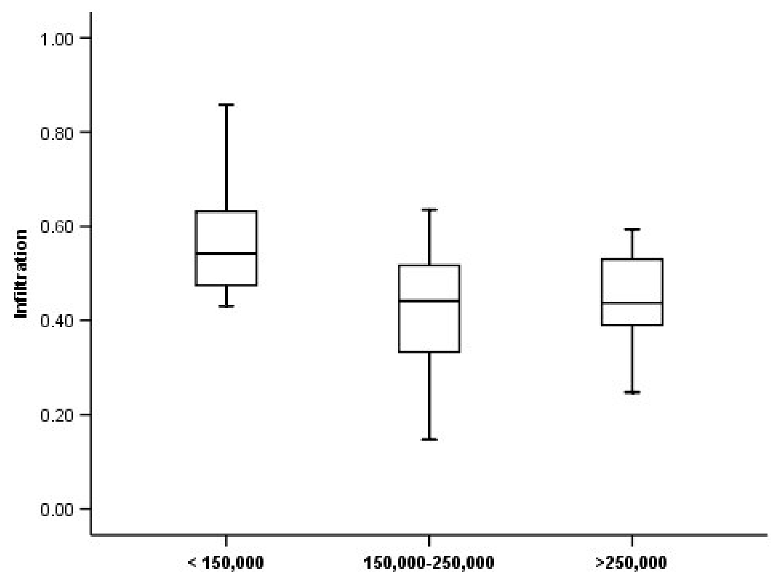

Figure 46. Distribution of residential infiltration values in the heating season for three improvement value classes.

Not surprisingly, a similar relationship was found between categorized total detached residential value based on medians and infiltration in the heating season (r=-0.291, p=0.073). The decrease in the strength of the relationship may be due in part to total value representing land value more than building value, which will decrease the relationship with infiltration as land value should not affect residential infiltration.

5.2.3.5 Multivariate Residential $PM_{2.5}$ Infiltration Model

For all residential types, a limited number of variables are available to model residential infiltration. Residential class was not significantly correlated to infiltration; therefore, a yearly infiltration model was created based solely on meteorological conditions. The resulting stepwise regression model included temperature, which predicted 39 percent of infiltration variation. A dichotomous heating and non-heating season variable explained 33 percent (p<0.000) of infiltration variation:

$$Infiltration_{(all\ residences)} = 0.733 + (-0.242)*(Season)$$

where season equals 1 for the heating season and 0 for the non-heating season.

Meteorological conditions and seasonality also predicted a larger portion of infiltration for only detached residences. Table 24 summarizes univariate regression statistics for infiltration, seasonal variables and meteorology for detached residences.

Table 24. Yearly, seasonal and meteorological variables and detached infiltration.

Variable	Description	Const.	Coef.	r^2	p	n
Month[a]	Integer 1-12 (quadratic)	0.206	0.17/-0.01	0.391	*0.000**	84
H/NH Season	(Oct-Feb)=1; (March-Sept)=0	0.728	-0.248	0.364	*0.000**	84
Temperature	Integer (degrees Celsius)	0.310	0.030	0.400	*0.000**	84
Precipitation	Integer (mm)	0.627	-0.004	0.097	*0.034**	45
Wind Speed	Integer (m/s)	0.629	-0.015	0.006	0.493	84
Relative Humidity	Integer (%)	1.054	-0.006	0.064	*0.020**	84

[a] Quadratic equation *Significantly (p<0.05)

Multivariate stepwise regression of meteorological variables and infiltration again resulted in only one variable, temperature, which predicted 40 percent of infiltration variation. A dichotomous heating and non-heating season variable explained 36 percent ($p<0.000$) of infiltration variation for detached residences, similar to the seasonal model reported previously.

$$Infiltration_{(detached\ residences)} = 0.728 + (-0.248)*(Season)$$

where season equals 1 for the heating season and 0 for the non-heating season.

Residential detached homes provided further opportunities to model $PM_{2.5}$ infiltration as additional information are available for housing characteristics from SPAD. Previous analysis revealed housing characteristics and infiltration were significantly correlated only in the heating season, potentially because high air exchange rates in the summer masked the effects of housing characteristics. Below is a multivariate model for the heating season, which includes only housing characteristics as broad meteorological conditions are captured by the heating season variable. In addition, the purpose of this model is to explain within region differences in infiltration, which will be affected more by housing characteristics than by meteorological conditions that are relatively uniform within the GBPS airshed.

Stepwise regression resulted in a model incorporating low improved residential value (<150,000) and oil or gas heating source. The model (R^2=0.38, $p<0.000$) is shown below:

$$Infiltration_{(Detached\ residences,\ HS)} = 0.359 + 0.158*(Improved.\ Value<150{,}000) + 0.101*(Oil/Gas\ heat)$$

where residential improved valued < 150,000 =1 and residential heating source as either oil or gas =1.

The final model explains a significant portion of residential detached infiltration in the heating season. Table 25 summarizes the resulting infiltration factors for the different model parameters. For example, if a home had a low improved value (<150,000) and was heating by oil or gas it would get an infiltration value of 0.618, while a house that had only a low improved value but was heated with electric baseboards would get an infiltration value of 0.517. The categorical variables included in the model allow the model to be applied from basic data inputs.

Table 25. Detached residential infiltration model results.

Model Parameter	Average Infiltration
Heating Season	
Improved Value < $150,000 & Oil or Gas Heat	0.618
Improved Value < $150,000	0.517
Oil and Gas Heat	0.460
All other detached residences	0.359
Non-Heating Season	0.728

Infiltration values resulting from the above models for the heating and non-heating seasons produce a range in infiltration factors of 0.359 to 0.728, while in the heating season the variability of infiltration could range from 0.359 to 0.618. These infiltration results produce significant variability in residential infiltration factors that will have large affects on exposure predictions.

5.2.3.6 Infiltration Model Sensitivity

This research presents an exploratory analysis of the potential to model residential $PM_{2.5}$ infiltration for use in exposure assessments. Due to small sample size results must be interpreted with caution.

A sensitivity analysis of the infiltration model created for detached residences was undertaken using a bootstrap approach. The sample was not large enough to leave half the samples out when building the model to then test the reliability of the model; however, when developing the model most variables were examined separately for both the Seattle and Victoria samples. Again, due to small sample size some housing characteristics could only be examined in the pooled sample.

The S-PLUS software was used to run the bootstrap analysis for both the detached seasonal and heating season models. One thousand new samples were selected (with replacement), each of the same size as the observed data. The 1000 re-samples are drawn because this is the recommended minimum for estimating confidence interval for model results. The regression result is calculated using each of the new samples, yielding a bootstrap distribution of the statistics of mean r^2 results.

The analysis of the season detached model indicates that season is a relatively stable variable in this sample for predicting infiltration. The bootstrap analysis resulted in a mean $r^2$of 0.37 (actual model results r^2= 0.36) with a standard error of 0.08. The results of the bootstrap analysis of the heating season model of building characteristics yielded a mean $R^2$of 0.39 (actual model results R^2= 0.38) with a standard error of 0.11. The percentiles were calculated for both models and are shown in Table 26. The distribution of the heating season model results from the bootstrap analysis is shown in Figure 47.

Table 26. Distribution of predicted r^2 from bootstrap analysis (percentiles).

	2.5%	**5%**	**25%**	**75%**	**95%**	**97.5%**
Seasonal Model r^2	0.19	0.21	0.29	0.41	0.49	0.51
HS Model R^2	0.16	0.20	0.31	0.47	0.58	0.62

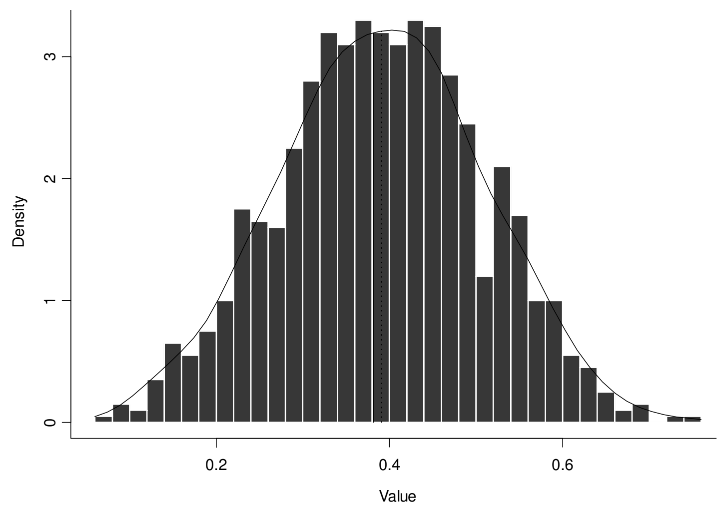

Figure 47. Distribution of heating season model results from bootstrap analysis.

Results of the bootstrap analysis reveal that the seasonal infiltration model and the infiltration model for the heating season are relatively stable (standard errors of 0.08 and 0.11). Nevertheless, more research is needed to examine the relationships between housing characteristics and infiltration in a larger sample of infiltration measurements. National air exchange databases may hold promise for examining the relationships between housing characteristic and air exchange, and in turn, what this means for residential infiltration.

6 Discussion

6.1 CRD Residential I/O $PM_{2.5}$ and Exposure Error

Outdoor $PM_{2.5}$ was a poor predictor of residential indoor $PM_{2.5}$ in the CRD. The variability of outdoor $PM_{2.5}$, indoor $PM_{2.5}$ sources and residential infiltration led to weak associations between I/O $PM_{2.5}$. One hour I/O $PM_{2.5}$ monitoring data were not correlated and five days mean outdoor $PM_{2.5}$ predicted only 31 percent of indoor $PM_{2.5}$, suggesting that outdoor $PM_{2.5}$ is not a suitable proxy for residential indoor exposure in epidemiological studies. This finding supports previous studies on I/O $PM_{2.5}$ relationships (Janssen et al. 2001; Kousa et al. 2002; Rea et al. 2001).

The average outdoor $PM_{2.5}$ level in the CRD (8.45ug/m^3) was low in comparison to nearby cities (e.g. Vancouver 13.21ug/m^3) although the average concentration during the heating season (10.16ug/m^3) was comparable. The current Health Canada standard for ambient $PM_{2.5}$ is the 90th percentile of monitored values exceeding 30ug/m^3 for a 24-hr average. This standard was not exceeded during any monitoring event; however, several households experienced extremely high, short-term indoor $PM_{2.5}$ episodes, which caused indoor concentrations to be greater than outdoor levels.

Indoor residential $PM_{2.5}$ was extremely variable within residences, between residences, and between monitoring events of the same residence. Average indoor $PM_{2.5}$ was 7.70 +/-3.90ug/m^3, the average 10th percentile was 3.64ug/m^3 and the 90th percentile was 13.14ug/m^3. Between the heating and non-heating seasons average indoor $PM_{2.5}$ was not significantly different, contrasting the significant difference found between outdoor $PM_{2.5}$ for the two seasons. The five days I/O ratio during the heating season was 0.96 and in the non-heating season was 1.10. Even though outdoor $PM_{2.5}$ was lower in the non-heating season than in the heating season, indoor concentrations were similar due to changes in residential infiltration.

Diurnal patterns of I/O $PM_{2.5}$, shown in Figure 48, illustrate the relationship between I/O $PM_{2.5}$ and how it changes throughout the day. Hourly average indoor $PM_{2.5}$ for all monitoring events was less than outdoor $PM_{2.5}$ from 21:00 to 7:00 when indoor sources are typically absent. During the day however differences between indoor behaviours caused large distributions within indoor $PM_{2.5.}$

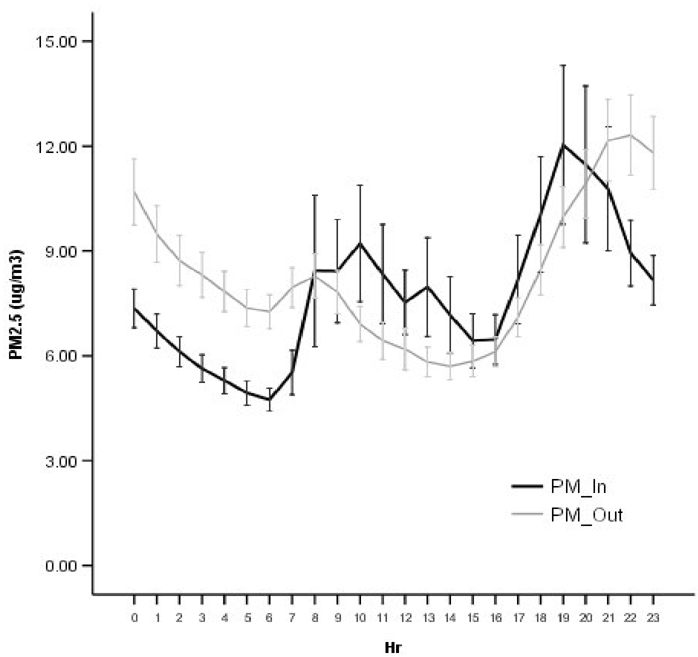

Figure 48. Hourly I/O $PM_{2.5}$ and 95% confidence intervals.

The majority of studies examining residential I/O $PM_{2.5}$ have characterized between day variations, such as daily correlations and I/O ratios, while little research has examined within day variation. The use of continuous monitors allowed this study to examine how indoor $PM_{2.5}$ corresponds to outdoor $PM_{2.5}$ throughout the day. Relatively stable indoor $PM_{2.5}$ and I/O $PM_{2.5}$ ratios during the night (23:00-6:00), shown previously in Figure 48, indicate that epidemiological studies may represent indoor $PM_{2.5}$ for this period with simple I/O ratios. For the CRD this ratio is 0.81. The remainder of the day however poses a number of challenges for predicting indoor $PM_{2.5}$. Daytime levels (7:00-23:00) were 35% higher than overnight periods (heating season 23%, non-heating season 51%) corresponding to the PTEAM study which found indoor $PM_{2.5}$ was 30% higher in the daytime compared to overnight periods (Ozkaynak et al. 1996).

Analysis of indoor $PM_{2.5}$ and housing characteristics, indoor activities and socio-economic factors revealed that total indoor $PM_{2.5}$ could not be accurately predicted. Detailed information is required on all activities within a home, for example cooking, cleaning and heating, to determine the contribution of indoor generated $PM_{2.5}$ to indoor levels. The variability of indoor $PM_{2.5}$, combined with similar variability in I/O $PM_{2.5}$ ratios, made it very difficult to predict indoor total $PM_{2.5}$. Conversely to indoor sources, filtration by residential buildings also caused variation in indoor $PM_{2.5}$ levels. In the CRD filtration caused indoor $PM_{2.5}$ to be less than outdoor ambient levels for 43 of the 73 monitoring events.

The analysis of I/O $PM_{2.5}$ in the CRD revealed that outdoor ambient $PM_{2.5}$ is not correlated to total indoor levels and therefore is a poor proxy for total exposure. Predicting total indoor generated $PM_{2.5}$ was not possible due to the random nature of indoor activities and resulting $PM_{2.5}$ sources. Higher correlations between I/O $PM_{2.5}$ in the absence of indoor sources revealed that the amount of indoor ambient $PM_{2.5}$ (infiltrated $PM_{2.5}$) could be modelled and would result in substantial improvements to predicted ambient $PM_{2.5}$ exposure.

6.2 Residential $PM_{2.5}$ Infiltration and Exposure Error

No significant difference was found between the Seattle and CRD infiltration samples, which allowed the two datasets to be combined into one residential sample (n=122) to further examine the effects of infiltration on exposure assessment and to predict infiltration with meteorological variables and building characteristics from SPAD. Average infiltration for the combined sample was 0.61 +/-0.21, indicating that on average approximately 61 percent of outdoor $PM_{2.5}$ penetrates inside residences and remains suspended.

Significant differences were found between infiltration during the heating (0.49) and non-heating (0.72) seasons. Meteorological conditions were highly correlated to infiltration (temperature and infiltration r=0.74, relative humidity and infiltration r=0.13 and precipitation and infiltration r=0.15) as meteorological conditions were found to be a good surrogate for window opening behaviours. Figure 49 illustrates the difference between infiltration percentiles in the heating and non-heating seasons.

During the heating season, infiltration was low due to residents keeping their windows closed, while in the non-heating season infiltration was higher because windows were left open to cool and ventilate residences. A heating and non-heating season variable for all residences predicted thirty six percent of the variation in infiltration. This stratification is important if ambient pollution levels vary from season to season, such as in the GBPS, if epidemiological studies are examining seasonal health outcomes or if population groups have different activity patterns between the two seasons.

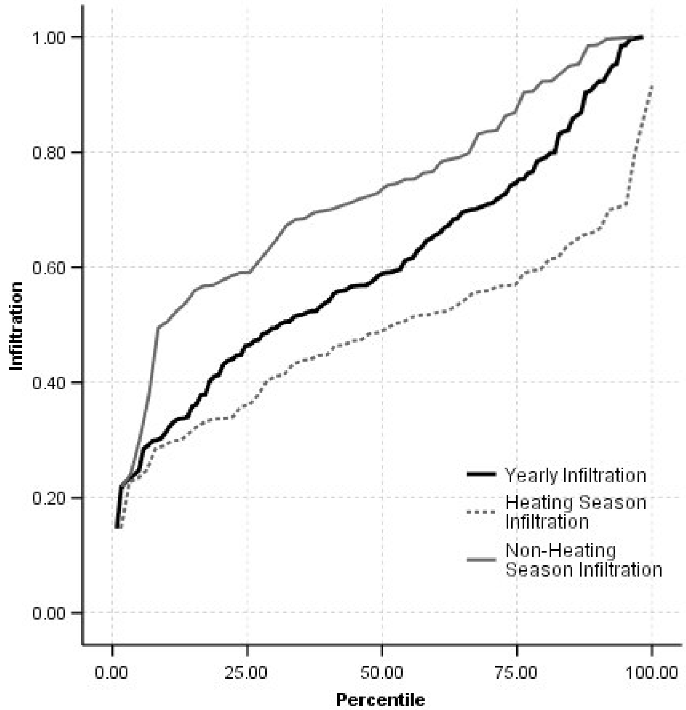

Figure 49. Yearly and HS/NHS residential infiltration percentiles.

Epidemiology studies examining the health effects of $PM_{2.5}$ through multiple city studies may also incorporate significant exposure error by not accounting for climate affects on infiltration. For example, Wallace and Williams (2005) found sulphur-based infiltration factors in North Carolina were lowest (0.50) in the summer and highest (0.63) in the other seasons, while in Seattle and the CRD infiltration in the non-heating season (0.72) was significantly higher than the heating season (0.49). Use of air conditioners most likely led to the seasonal differences as they significantly alter infiltration factors in the summer by reducing residential air exchange. Unfortunately, air conditioning is not included in all SPAD. King County collects information on air conditioners; however, BC assessment data and Snohomish County do not collect this information. In Victoria and Seattle few residences have air conditioning units; therefore, air conditioners are not a significant modifier of exposure to $PM_{2.5}$ in this region.

Meteorological data could be used as a surrogate for air conditioner use in epidemiological studies. Apte et al. (1998) compiled meteorological data for the continental United States, which could be used to predict air conditioner use and applied to indoor air pollution models. Figure 50 illustrates derived annual heating infiltration degree days for the continental United States, representing the degree to which temperature and wind will affect ventilation rates in homes. The creation of a similar database in Canada, and possibly at a more detailed scale, would be useful for predicting climates roles in modifying residential infiltration factors through the use of air conditioning systems and different window opening behaviours.

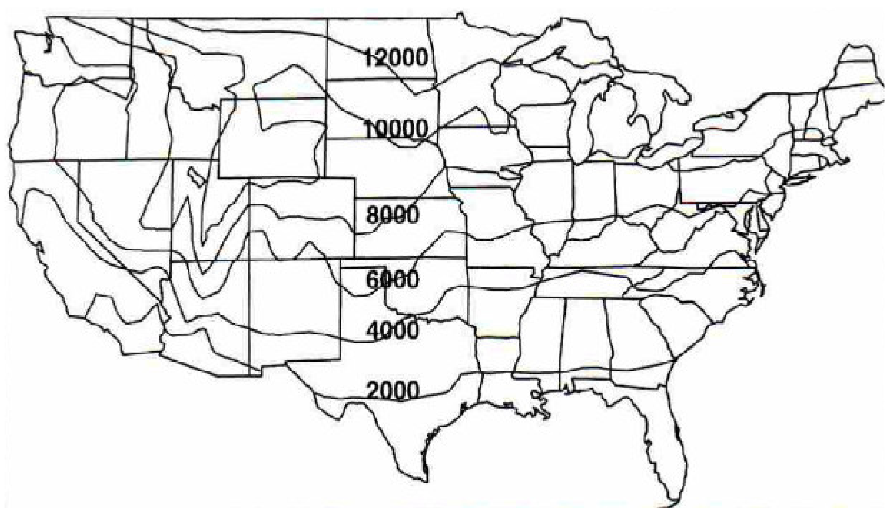

Figure 50. Annual heating infiltration degree days (Apte et al. 1998).

In terms of regional epidemiological studies such as the Health Canada funded BAQS, it is unlikely that meteorological conditions will incorporate significant spatial variation in residential infiltration as meteorological conditions are fairly uniform within the study region. Applying temperature as a predictor of infiltration will therefore systematically lower or raise infiltration factors, but will not produce differences between residences, unless air conditioners are used in homes and window opening behaviours differ. Unfortunately, data are not available for these two parameters.

Building characteristics accounted for a portion of within region variation in Seattle and CRD infiltration factors. No significant differences were found for different classes of residences; however, associations suggested that detached residences have slightly lower infiltration than other types of residences, particularly apartments and condominiums. Figure 51 illustrates the infiltration percentiles for detached homes and non-detached homes.

It appears that apartments and condominiums have higher infiltration factors than detached homes. Drawing on literature, detached residences may have lower infiltration compared to apartments and condominiums because of greater volumes and physical construction (Chan et al. 2005; Ozkaynak et al. 1996). For example, apartments typically have smaller volumes, and therefore will have higher air exchange rates and in turn infiltration. Apartments may also have increased infiltration due to infiltration from neighbouring units. This was evident in one monitoring event in the CRD where smoking in a lower unit elevated indoor $PM_{2.5}$ levels above outdoor ambient levels for the entire five days monitoring period. This monitoring event was one of the eleven removed from analysis. While the difference in infiltration between detached residences and apartment and condominiums is small, apartments and condominiums tend to be located in areas that have higher air pollution, which in combination with higher infiltration factors will lead to significant exposure misclassification.

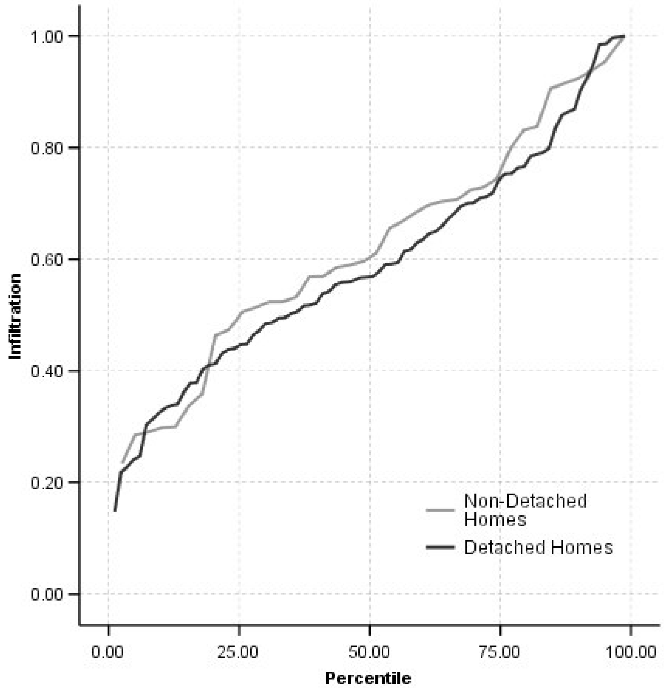

Figure 51. Infiltration percentiles for detached and non-detached homes.

SPAD was used to analyze the number of apartments within 200 meters of major roads (higher pollution areas) as a percentage of all apartments within a region. Table 27 summarizes results for the CRD, as well as Vancouver, Burnaby, and Richmond. These areas were selected to examine whether similar patterns emerged in different residential locations. Results indicate that detached homes are less likely to be within 200 meters of a major road and are therefore less likely to be exposed to higher ambient pollution concentrations.

Table 27. Percent of residential types within 200 meters of a major road.

	Detached	**Apartments/Condos**
CRD	21071 (33%)	2196 (46%)
Vancouver	44452 (58%)	16257 (76%)
Burnaby	12509 (45%)	1354 (59%)
Richmond	10498 (39%)	7394 (47%)

*Major road includes highways, freeways, arterials and collectors.

Figure 52 illustrates all apartment locations for Vancouver and a land use regression model indicating locations of high NO_2 concentrations. Clearly, there is a tendency for apartments to be located in high pollution areas. Higher infiltration, even as low as 0.04, may therefore have a larger impact on exposure than previously thought when outdoor $PM_{2.5}$ levels are considered.

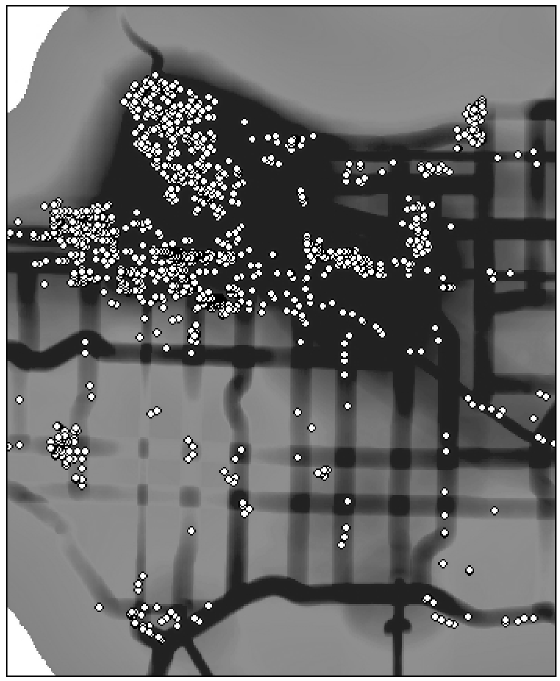

Figure 52. Location of apartment and condominiums in Vancouver and NO_2 landuse regression predictions.

Further examination of the effects of building structures for all residences was not possible because of the lack of SPAD for non-detached residences. British Columbia's SPAD does not collect individual data on apartment and condominium units; however, some assessors' offices in the United States collect information on every residential unit, independent of residential type. Future studies could therefore incorporate housing characteristics for residences other than detached homes.

Analysis of detached residences and SPAD housing characteristics revealed a number of significant associations. During the non-heating season infiltration was driven largely by residents opening their windows, which masked any influence of building characteristics. During the heating season however residential age, square footage, heating source, condition, and improved value were all associated with infiltration. Older residences had higher infiltration factors than newer homes, particularly before and after 1980, when building standards changed to promote energy efficient homes. Increased residential square footage was associated with lower infiltration factors, which results from higher air exchange rates in residences with smaller volumes. Residences classed as being in less than good condition within SPAD also had higher infiltration factors. Low improved value residences (<$150,000) were also associated with higher infiltration. Interestingly, the range of infiltration values in the non-heating season (0.78) was similar to the heating season (0.76), suggesting that window opening behaviours and households characteristics create significant variability in infiltration during both seasons.

Stepwise regression of building characteristics during the heating season resulted in a mixed effect model that predicted 38% of the variance in infiltration and included improved residential value and heating source as either oil or gas. Figure 53 illustrates the difference in infiltration between homes with oil and gas heating and low improved value and homes without these building characteristics.

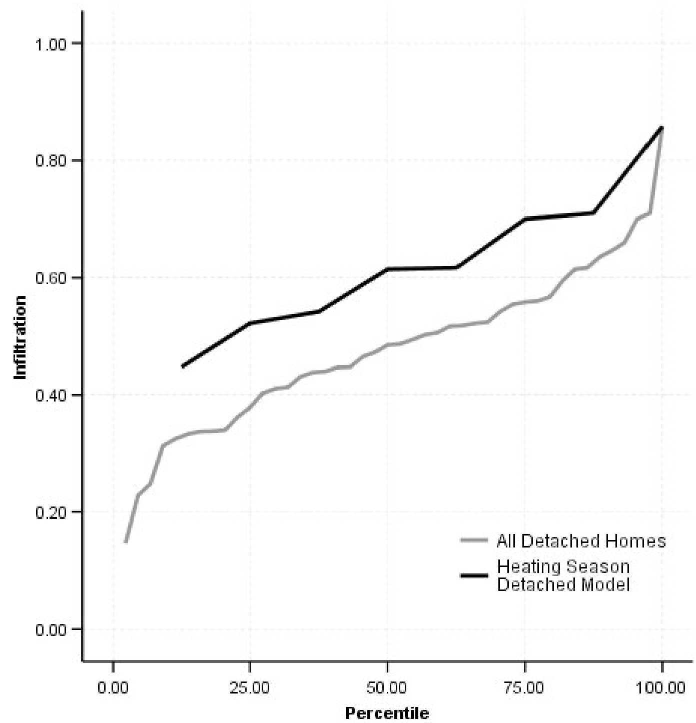

Figure 53. Infiltration percentiles for detached heating season model and all detached residences.

Different housing characteristics tended to be highly correlated, which resulted in stepwise regression removing a number of housing characteristics that were significantly related to infiltration in univariate analysis. For example, improved value was correlated with age, square footage and residential condition, which resulted in these variables being removed in stepwise regression. Since improved residential value is a combination of year built, size of home and condition of home, it is a powerful variable for predicting residential infiltration.

The oil and gas heat source variable raises the question to whether this is an indoor source of $PM_{2.5}$ that was not censored correctly, due to continuous and low emissions, or if the variable is increasing residential air exchange through forced hot air mechanisms. Oil and gas heating mechanisms emit more $PM_{2.5}$ than electric methods and may increase air exchange through the presence of ducts or through increasing thermal I/O gradients (Sherman and Chan, 2004); however, Hanninen et al. (2004) found that use of gas appliances were not significantly related to indoor $PM_{2.5}$ (r^2=0.01, p=0.43). Certain types of newer furnaces also introduce fresh air into homes, rather than recirculating air. Homes that use oil or gas for heating may therefore have higher infiltration factors than homes that use other heating methods, such as electric baseboard heaters, due to increased air exchange rates.

Improved value refers to the value of the building itself and does not include land values. When determining improved value of a residence assessors look at the size and age of the building, and the condition of the building (all variables that were significantly related to infiltration). Stratifying improved value into low (<$150,000), medium (150,000-250,000) and high (>250,000) resulted in low improved value alone explaining 28% of infiltration variation. Figure 54 indicates the percentiles for infiltration by the three improved stratifications during the heating season.

Improved value as a predictor of $PM_{2.5}$ infiltration has a number of important implications for epidemiological studies, as well as for environmental equity and social justice research. The majority of literature examining SES and air pollution exposure has focused on low SES individuals being located in areas that have higher ambient air pollution (Jerret et al. 2004; Gunier et al. 2003), rather than how SES may influence other exposure routes. This is the first study that has found links between building characteristics (low improved value), a likely indicator of low SES, and increased exposure to air pollution.

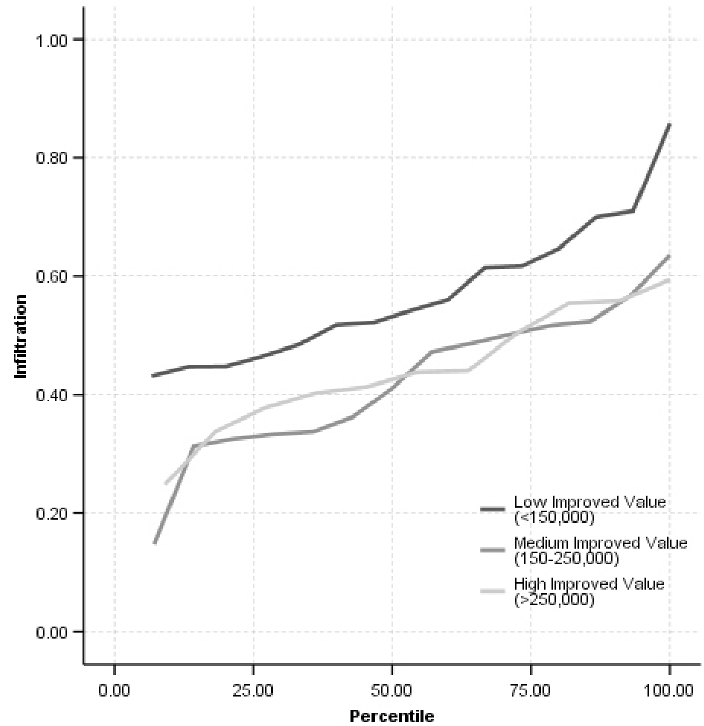

Figure 54. Infiltration percentile stratified by detached improved value.

Individuals living in low improved value detached homes had average infiltration factors 0.15 higher than improved valued homes (>$150,000) in the heating season. Individuals living in these homes may also experience a similar impact as those individuals living in apartments, as a number of studies have found low SES homes are more likely to be located in higher polluted areas (Jerret et al. 2004; Gunier et al. 2003). If homes with lower improved values are also located in higher polluted areas, the impact of higher infiltration factors on exposure error would be even greater, due to higher outdoor pollution levels.

In the CRD, regression of improved and total detached residential value resulted in an $r^2=0.652$, $p<0.000$. Total residential value can be used to determine SES, and in the CRD, total value correlated well ($r=0.89$, $p<0.00$) to household income at the census block level. Individuals' who rent rather than own their homes is an obvious limitation of this approach.

Similar to apartments, an analysis of distance from major roads was conducted using SPAD to examine if lower improved value homes were more likely to be located in higher polluted areas. Table 28 indicates that less improved value homes are in fact more likely to be located in higher polluted areas, particularly in larger urban areas. For example, in the Vancouver area 60 percent of all homes with improved value under $50,000 are located within 200 meters of a major road, while only 49 percent of homes with improved values over $250,000 are located in these areas.

Table 28. Location of stratified detached improved value and major roads.

	<50,000	**50,000-100,000**	**100,000-150,000**	**150,000-200,000**	**200,000-250,000**	**>250,000**
CRD	39%	55%	55%	32%	27%	26%
Vancouver	60%	58%	58%	59%	54%	49%
Burnaby	48%	43%	44%	41%	41%	40%
Richmond	40%	40%	39%	38%	38%	38%

The infiltration models created in this research can be applied to epidemiology studies to improve predictions of personal exposure to ambient $PM_{2.5}$. The best approach to incorporating infiltration would be to link health records with exposure data using residential addresses. An infiltration model based on SPAD data could therefore easily be incorporated into individual exposure analysis as SPAD is available for every residential address in the GBPS. Unfortunately, due to privacy issues, health data are rarely provided at the individual level. In the GBPS epidemiological analysis, health data are enumerated to six digit postal codes. Figure 55 illustrates the resolution of cadastral data, six digit postal codes (centroids), and dissemination areas. Boundaries for six digit postal codes do not currently exist in BC.

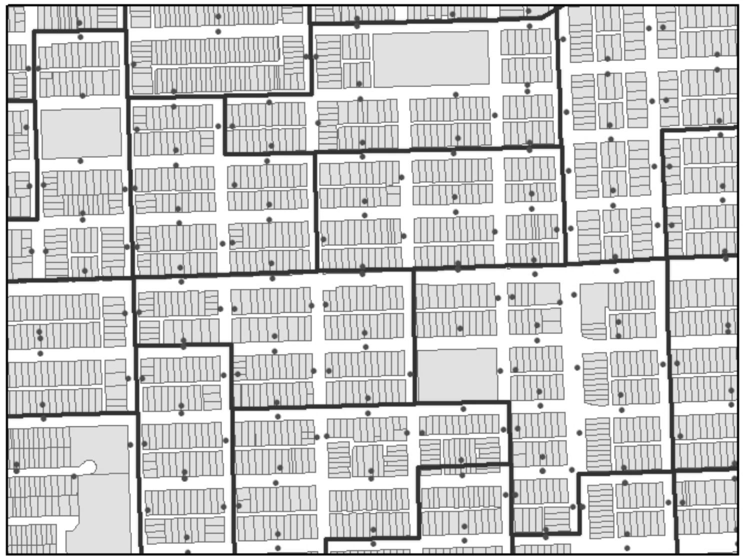

Figure 55. Spatial resolution of cadastral data, six digit postal codes and dissemination areas in Vancouver.

Aggregating residential infiltration factors is not ideal, since infiltration factors vary from one residence to the next; however, infiltration factors could be aggregated if there are distinct regions that have small variations within their enumerated boundary. Epidemiology studies need to begin to use individual residential addresses as the basis for linking exposure and health data as significant improvements in exposure predictions could be made by such incorporation of individual building characteristics and the affects they have on $PM_{2.5}$ infiltration.

Overall, this study was able to produce infiltration models that predict a large portion of residential $PM_{2.5}$ infiltration in the GBPS airshed. For all residences a heating and non-heating season variable was important for explaining the major differences in infiltration caused by meteorological conditions. For detached residences, a heating and non-heating variable explained 36% of the variation in residential infiltration and a separate model, based on SPAD housing characteristics, predicted 38% of infiltration in the heating season. In the non-heating season, one infiltration factor may be used as no housing characteristics were significantly associated with infiltration; however, in regions with a high percentage of residences using air conditioners, significant differences will result between these homes and homes with natural ventilation.

7 Conclusions

Epidemiological research that uses outdoor $PM_{2.5}$ as a proxy for total personal exposure incorporate significant error into exposure classification by not accounting for differences caused by residential infiltration. In the CRD, indoor and outdoor $PM_{2.5}$ was poorly correlated. To illustrate, the results show that 43 homes had lower indoor $PM_{2.5}$ than outdoor ambient levels and 30 homes had higher indoor $PM_{2.5}$. In the absence of detailed data on indoor activities, which generate a large portion of the indoor $PM_{2.5}$ variability, infiltration factors are a realistic mechanism for improving exposure predictions of indoor ambient $PM_{2.5}$.

Large seasonal variations were found in residential infiltration that has potentially large implications for epidemiology studies examining the health impacts of $PM_{2.5}$ through multiple city study designs. Similarly, meteorological conditions were a powerful predictor of yearly infiltration change. Further research is required to sample residential infiltration in homes within different climate regions to examine seasonal infiltration patterns. It is hypothesized that seasonal patterns of $PM_{2.5}$ infiltration will change significantly with different climatic conditions, especially in hot and humid regions that promote the use of air conditioners.

The GBPS airshed has a relatively uniform climate; therefore, seasonality and the effects of meteorological variables alone will not incorporate significant variability within infiltration between residences. Applying a seasonal adjustment factor will increase or decrease exposure for all residences. This does not hold true for homes that use air conditioners; however, this consisted of few homes in the GBPS. Seasonal adjustments on infiltration factors will be important in determining the dose of $PM_{2.5}$, as it was shown in the CRD that indoor $PM_{2.5}$ levels were similar between seasons even though outdoor ambient $PM_{2.5}$ was 48 percent higher in the heating season than in the non-heating season. Seasonal adjustments may also be important when examining health endpoints that have a seasonal component, such as bronchitis.

For within region studies, building characteristics and indoor behaviours will produce the majority of differences found in residential infiltration. Indoor behaviours, particularly window opening behaviour, can be partially predicted with a heating and non-heating season variable, suggesting the need to develop separate infiltration models for the heating season (low residential air exchange) and for the non-heating season (high residential air exchange). Spatial property assessment data contained detailed building information only for detached residences in the GBPS; however, certain assessment regions do collect information on all residences, which provides opportunities to predict infiltration with building characteristics for all residences.

No significant predictors were found for detached residences in the non-heating season. The mean infiltration factor was 0.72+/-0.19 and the range of infiltration (0.78) was similar to the range found in the heating season. Significant exposure error will be incorporated into epidemiology studies by using one infiltration factor (0.72); however, the main factor determining the differences between homes, air conditioners and window opening behaviours during the summer, cannot be explained at this time.

During the heating season the multivariate regression model for detached residences explained 38 percent of the variation in infiltration, which included variables on improved value of the home and heat source as oil or gas. The model indicates that homes with these characteristics will have infiltration factors nearly 30% higher than homes that are of higher improved value or that use electric heating sources. This also raises environmental equity and social justice issues as lower improved value homes are likely located in higher ambient pollution areas.

This study made significant steps towards producing a residential infiltration model; however, this was an exploratory study with certain limitations. The main limitation of this study was sample size. A residential sample of 122 monitoring events is relatively large compared to other infiltration studies; however, the sample becomes much smaller when stratified by season and residential type. Larger sample sizes are needed to examine the specific housing characteristics identified in this research, specifically improved value and heating type. The large difference found between detached improved value under $150,000 needs to be expanded to examine if the pattern remains for homes of lesser improved value. This may incorporate more variance in residential infiltration and become even more pronounced within the lowest improved value homes. Further research is also required to examine differences between residential types, such as apartments, condominiums, and group homes, and the affects of housing characteristics on infiltration within these housing subgroups. In certain regions of the United States, SPAD contains information on these building types, which provide further opportunities for examining, and modelling infiltration. National energy programs that collect residential air exchange data may also be used to predict indoor ambient $PM_{2.5}$ as they are available for large regions and contain data for large numbers of residences.

In terms of public health and policy recommendations, this research has shown that in the Pacific Northwest, where ambient $PM_{2.5}$ levels are relatively low, indoor $PM_{2.5}$

is of greater concern than outdoor $PM_{2.5}$ for exposure potential. It is important to recognize that roughly 61% of outdoor $PM_{2.5}$ gets inside residences in the GBPS airshed, which then contributes to personal exposure. Indoor generated $PM_{2.5}$, specifically smoking, cooking, heating and cleaning, also have the potential to dramatically elevate indoor levels of $PM_{2.5}$, and other pollutants, above the Canadian Health standards guidelines. Considering individuals spend approximately seventy percent of their time indoors at home, important interventions and policy recommendations can be made to reduce residential exposure to $PM_{2.5}$ and other pollutants.

The most effective intervention over the long-term would be amending residential building codes to include mandatory mechanical ventilation systems with filtered air supply. This regulation was established in Finland in 2005, which was estimated through simulation studies to reduce population exposure to ambient $PM_{2.5}$ by approximately twenty seven percent (Hanninen et al. 2005a). Mechanical ventilation systems will also reduce indoor generated pollutants through greater air exchange rates. The reduction of $PM_{2.5}$ infiltration, and indoor generated $PM_{2.5}$, through filtration also has the advantage of reducing exposure to all types of particles, for example, particles originating from diesel trucks or industrial point sources, and may therefore be a more successful intervention, at least over the short term, than regulating emission sources. This becomes even truer when considering the current limitations to regulating automobiles and industrial sources. It will however take some time for the existing building stock in Canada to turn over to newer building with mechanical ventilation and filtered air; therefore, intermediate interventions also could be put in place to address indoor $PM_{2.5}$ and other pollutant exposures.

A number of interventions could be undertaken to address indoor $PM_{2.5}$ exposures over the short term. One of the foremost public health challenges faced when dealing with indoor pollution is the lack of knowledge surrounding potential health impacts of indoor pollutants and indoor sources of pollution. In the GBPS airshed the majority of the population are not overly concerned with air pollution, given the low levels of ambient pollution concentrations in the airshed, and therefore, the awareness of indoor pollution as a health threat is also low. This was demonstrated by several residences in this study who were not aware of indoor sources of $PM_{2.5}$ and how high indoor concentration of $PM_{2.5}$ could be elevated by such sources as cooking or heating with a wood stove. A general public education campaign targeting the entire population, not just susceptible populations, would have enormous benefits to reducing the health impacts of indoor air pollution.

Individuals who want to take action against indoor air pollution should have mechanisms available to them that reduce their exposure to indoor pollution. Such mechanisms could include incentives to buy air filters or air conditions, which reduce infiltration of $PM_{2.5}$ and other outdoor pollutants. These types of incentives have been established for other purposes, such as improving the energy efficiency of household appliances, and have had success. Mechanisms to reduce indoor air pollution, such as indoor air filters, should not be restricted to high SES individuals due to high costs. Programs must be put in place that allows all individuals, regardless of SES, location, or health status, to take action to reduce their exposure to pollutants in their home.

This research providS information that highlights the importance of the home environmental for exposure reduction, and shows that certain individuals, specifically those located in lower class housing, may be disproportionately exposed to outdoor pollution inside their home. Public health interventions could be established that reduce health disparities arising not only from ambient air pollution, but also from indoor generated air pollution. More work however is needed to translate research findings into policy and pubic health action.

8 Bibliography

Abbey, D.E., Nishino, N., McDonnell, W.F., Burchette, R.J., Knusten, S.F.,Beeson, W.L., Yang, J.X. (1999) Long-Term Inhalable Particles and Other Air Pollutants Related to Mortality in Nonsmokers; Am. J. Respir. Crit. Care Med. **159**, 373-382.

Abbey, D. E., S. D. Colome, P. K. Mills, R. Burchette, W. L. Beeson and Y. Tian (1993). Chronic Disease-Associated with Long-Term Concentrations of Nitrogen-Dioxide. Journal of Exposure Analysis and Environmental Epidemiology **3**(2): 181-202.

Abt, E., H. H. Suh, G. Allen and P. Koutrakis (2000). Characterization of indoor particle sources: A study conducted in the metropolitan Boston area. Environmental Health Perspectives **108**(1): 35-44.

Apte, M. G., A. V. Nero and K. L. Revzan (1998). Meteorological database for the United States. Indoor Air-International Journal of Indoor Air Quality and Climate **8**(1): 61-67.

Allen R., Wallace, L., Larson, T., Sheppard, L., and Liu, S. (2007) Evaluation of the recursive model approach for estimating particulate matter infiltration efficiencies using continuous light scattering data. Journal of Exposure Science & Environmental Epidemiology In Press.

Allen R, Larson T, Sheppard L, Wallace L, Liu L-JS (2003) Use of real-time light scattering data to estimated the contribution of infiltrated and indoor-generated particles to indoor air. Environ Sci Technol. **37**:3485–3492.

Atkinson, R. W., S. A. Bremner, H. R. Anderson, D. P. Strachan, J. M. Bland and A. P. de Leon (1999). Short-term associations between emergency hospital admissions for respiratory and cardiovascular disease and outdoor air pollution in London. Archives of Environmental Health **54**(6): 398-411.

Aunan, K. (1996). Exposure-response functions for health effects of air pollutants based on epidemiological findings. Risk Analysis **16**(5): 693-709.

BC Statistics (2002) Dwelling Characteristics and Household Equipment. http://www.bcstats.gov.bc.ca/

Boman, B. C., A. B. Forsberg and B. G. Jarvholm (2003). Adverse health effects from ambient air pollution in relation to residential wood combustion in modern society. Scandinavian Journal of Work Environment & Health **29**(4): 251-260.

Brauer, M., Hirtle, R., Lang, B., Ott, W. (2000). Assessment of indoor fine aerosol contributions from environmental tobacco smoke and cookingwith a portable nephelometer. Journal of Exposure Analysis and Environmental Epidemiology **10** (2), 136–144.

Bennett, D.H.; Koutrakis, P. (2006) Determining the infiltration of outdoor particles in the indoor environment using a dynamic model. Journal of Aerosol Science **37**, 766-785

Burke, J. M., M. J. Zufall and H. Ozkaynak (2001). A population exposure model for particulate matter: case study results for PM2.5 in Philadelphia, PA. Journal of Exposure Analysis and Environmental Epidemiology **11**(6): 470-489.

Burnett, R. T., S. Cakmak and J. R. Brook (1998). The effect of the urban ambient air pollution mix on daily mortality rates in 11 Canadian cities. Canadian Journal of Public Health-Revue Canadienne De Sante Publique **89**(3): 152-156.

Chan, W. Y. R., W. W. Nazaroff, P. N. Price, M. D. Sohn and A. J. Gadgil (2005). Analyzing a database of residential air leakage in the United States. Atmospheric Environment **39**(19): 3445-3455.

Chang, T. J., M. Y. Huang, Y. T. Wu and C. M. Liao (2003). Quantitative prediction of traffic pollutant transmission into buildings. Journal of Environmental Science and Health Part a-Toxic/Hazardous Substances & Environmental Engineering **38**(6): 1025-1040.

Chao, C. Y. H. and T. C. Tung (2001). An empirical model for outdoor contaminant transmission into residential buildings and experimental verification. Atmospheric Environment **35**(9): 1585-1596.

Colome, S.D., Kado, N.Y., Jaques, P., & Kleinman, M. (1992). Indoor-outdoor air pollution relations, particulate matter less than 10 μm in aerodynamic diameter (PM10) in homes of asthmatics. Atmos. Environ., **26A**, 2173-2178.

Dimitroulopoulou, C., M. R. Ashmore, M. A. Byrne and R. P. Kinnersley (2001). Modelling of indoor exposure to nitrogen dioxide in the UK. Atmospheric Environment **35**(2): 269-279.

Dockery, D. W., C. A. Pope, X. P. Xu, J. D. Spengler, J. H. Ware, M. E. Fay, B. G. Ferris and F. E. Speizer (1993). An Association between Air-Pollution and Mortality in 6 United-States Cities. New England Journal of Medicine **329**(24): 1753-1759.

Dockery, D. W. and J. D. Spengler (1981a). Indoor-Outdoor Relationships of Respirable Sulfates and Particles. Atmospheric Environment **15**(3): 335-343.

Dockery, D. W. and J. D. Spengler (1981b). Personal Exposure to Respirable Particulates and Sulfates. Journal of the Air Pollution Control Association **31**(2): 153-159.

Englert, N. (2004). Fine particles and human health - a review of epidemiological studies. Toxicology Letters **149**(1-3): 235-242.

Ezzati, M., Lopez, A.D., Rodgers, A., Hoorn, S., Murray, J.D. (2002). Selected major risk factors and global and regional burden of disease. The Lancet **360** (9393):1347-1360.

Georgopoulos, P. G., S. W. Wang, V. M. Vyas, Q. Sun, J. Burke, R. Vedantham, T. McCurdy and H. Ozkaynak (2005). A source-to-dose assessment of population exposures to fine PM and ozone in Philadelphia, PA, during a summer 1999 episode. Journal of Exposure Analysis and Environmental Epidemiology **15**(5): 439-457.

Giles-Corti, B., Donovan, R.J.(2002). Socioeconomic status differences in recreational physical activity levels and real and perceived access to a supportive physical environment. Prev. Med. **35**, 601–611.

Hanninen, O., H. Kruize, E. Lebret and M. Jantunen (2003). EXPOLIS simulation model: PM2.5 application and comparison with measurements in Helsinki. Journal of Exposure Analysis and Environmental Epidemiology **13**(1): 74-85.

Hanninen, O. O., E. Lebret, V. Ilacqua, K. Katsouyanni, F. Kunzli, R. J. Sram and M. Jantunen (2004). Infiltration of ambient PM2.5 and levels of indoor generated non-ETS PM2.5 in residences of four European cities. Atmospheric Environment **38**(37): 6411-6423.

Hanninen, O. O., J. Palonen, J. T. Tuomisto, T. Yli-Tuomi, O. Seppanen and M. J. Jantunen (2005a). Reduction potential of urban PM2.5 mortality risk using modern ventilation systems in buildings. Indoor Air **15**(4): 246-256.

Hanninen, O. O., J. T. Tuomisto and M. J. Jantunen (2005b). Characterization of model error in a simulation of fine particulate matter exposure distributions of the working age population in Helsinki, Finland. Journal of the Air & Waste Management Association **55**(4): 446-457.

Hirsch, T., S. K. Weiland, E. von Mutius, A. F. Safeca, H. Grafe, E. Csaplovics, H. Duhme, U. Keil and W. Leupold (1999). Inner city air pollution and respiratory health and atopy in children. European Respiratory Journal **14**(3): 669-677.

Hoek, G., B. Brunekreef, S. Goldbohm, P. Fischer and P. A. van den Brandt (2002). Association between mortality and indicators of traffic-related air pollution in the Netherlands: a cohort study. Lancet **360**(9341): 1203-1209.

Janssen, N. A. H., J. Schwartz, A. Zanobetti and H. H. Suh (2002). Air conditioning and source-specific particles as modifiers of the effect of PM10 on hospital admissions for heart and lung disease. Environmental Health Perspectives **110**(1): 43-49.

Janssen, N. A. H., P. H. N. van Vliet, F. Aarts, H. Harssema and B. Brunekreef (2001). Assessment of exposure to traffic related air pollution of children attending schools near motorways. Atmospheric Environment **35**(22): 3875-3884.

Johnson, T., J. Myers, T. Kelly, A. Wisbith and W. Ollison (2004). A pilot study using scripted ventilation conditions to identify key factors affecting indoor pollutant concentration and air exchange rate in a residence. Journal of Exposure Analysis and Environmental Epidemiology **14**(1): 1-22.

Jones, A. P. (1999). Indoor air quality and health. Atmoshperic Environment **33**: 4535-4564.

Kappos, A. D., P. Bruckmann, T. Eikmann, N. Englert, U. Heinrich, P. Hoppe, E. Koch, G. H. M. Krause, W. G. Kreyling, K. Rauchfuss, P. Rombout, V. Schulz-Klemp, W. R. Thiel and H. E. Wichmann (2004). Health effects of particles in ambient air."International Journal of Hygiene and Environmental Health **207**(4): 399-407.

Keeler, G. J., M. Morishita and L. H. Young (2005). Characterization of complex mixtures in urban atmospheres for inhalation exposure studies. Experimental and Toxicologic Pathology **57**: 19-29.

Klepeis, N. E., W. C. Nelson, W. R. Ott, J. P. Robinson, A. M. Tsang, P. Switzer, J. V. Behar, S. C. Hern and W. H. Engelmann (2001). The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. Journal of Exposure Analysis and Environmental Epidemiology **11**(3): 231-252.

Kousa, A., J. Kukkonen, A. Karppinen, P. Aarnio and T. Koskentalo (2002). A model for evaluating the population exposure to ambient air pollution in an urban area. Atmospheric Environment **36**(13): 2109-2119.

Kousa, A., C. Monn, T. Rotko, S. Alm, L. Oglesby and M. J. Jantunen (2001). Personal exposures to NO2 in the EXPOLIS-study: relation to residential indoor, outdoor and workplace concentrations in Basel, Helsinki and Prague. Atmospheric Environment **35**(20): 3405-3412.

Koutrakis, P., S. L. K. Briggs and B. P. Leaderer (1992). Source Apportionment of Indoor Aerosols in Suffolk and Onondaga Counties, New-York. Environmental Science & Technology **26**(3): 521-527.

Kruize, H., O. Hanninen, O. Breugelmans, E. Lebret and M. Jantunen (2003). Description and demonstration of the EXPOLIS simulation model: Two examples of modeling population exposure to particulate matter. Journal of Exposure Analysis and Environmental Epidemiology **13**(2): 87-99.

Laden, F., L. M. Neas, D. W. Dockery and J. Schwartz (2000). Association of fine particulate matter from different sources with daily mortality in six US cities. Environmental Health Perspectives **108**(10): 941-947.

Leech, J. A., M. Raizenne and J. Gusdorf (2004). Health in occupants of energy efficient new homes. Indoor Air **14**(3): 169-173.

Letz. R., Ryan, P.B., and Spengler, J.D. (1984). Estimated distributions of personal exposures to respirable particles, Environmental Monitoring and Assessment **4**:351-359.

Lioy, P.J., Waldman, J.M., Buckley, T., Butler, J., & Pietarinen, C. (1990). The personal, indoor and outdoor concentrations of PM10 measured in an industrial community during the winter. Atmos. Environ. **24**B(1), 57-66.

Lipfert, F. W., S. C. Morris and R. E. Wyzga (2000). Daily mortality in the Philadelphia metropolitan area and size-classified particulate matter. Journal of the Air & Waste Management Association **50**(8): 1501-1513.

Liu, S. L., D. Krewski, Y. L. Shi, Y. Chen and R. T. Burnett (2003). Association between gaseous ambient air pollutants and adverse pregnancy outcomes in Vancouver, Canada. Environmental Health Perspectives **111**(14): 1773-1778.

Liu, L.-J. S.; Box, M.; Kalman, D.; Kaufman, J.; Koenig, J.; Larson, T.; Sheppard, L.; Wallace, L. (2003) Exposure assessment of particulate matter for susceptible populations in Seattle. Environ. Health Perspect. **111**, 909-918.

Long, C. M. and J. A. Sarnat (2004). Indoor-outdoor relationships and infiltration behavior of elemental components of outdoor PM2.5 for Boston-area homes. Aerosol Science and Technology **38**: 91-104.

Mather, F. J., L. E. White, E. C. Langlois, C. F. Shorter, C. M. Swalm, J. G. Shaffer and W. R. Hartley (2004). Statistical methods for linking health, exposure, and hazards. Environmental Health Perspectives **112**(14): 1440-1445.

McConnell, R., K. Berhane, F. Gilliland, S. J. London, H. Vora, E. Avol, W. J. Gauderman, H. G. Margolis, F. Lurmann, D. C. Thomas and J. M. Peters (1999). Air pollution and bronchitic symptoms in Southern California children with asthma. Environmental Health Perspectives **107**(9): 757-760.

Meng, Q. Y., B. J. Turpin, A. Polidori, J. H. Lee, C. Weisel, M. Morandi, S. Colome, T. Stock, A. Winer and J. F. Zhang (2005). PM2.5 of ambient origin: Estimates and exposure errors relevant to PM epidemiology. Environmental Science & Technology **39**(14): 5105-5112.

Monn, C. (2001). Exposure assessment of air pollutants: a review on spatial heterogeneity and indoor/outdoor/personal exposure to suspended particulate matter, nitrogen dioxide and ozone. Atmospheric Environment **35**(1): 1-32.

Monn, C., A. Fuchs, D. Hogger, M. Junker, D. Kogelschatz, N. Roth and H. U. Wanner (1997). Particulate matter less than 10 mu m (PM10) and fine particles less than 2.5 mu m (PM2.5): relationships between indoor, outdoor and personal concentrations. Science of the Total Environment **208**(1-2): 15-21.

Mosley, R.B., Greenwell, D.J., Sparks, L.E., Guo, Z., Tucker, W.G., Fortmann, R., Whitfield, C. (2001). Penetration of ambient fine particles into the indoor environment. Aerosol Science and Technology **34**, 127–136.

Nazaroff, W. W. (2004). Indoor particle dynamics. Indoor Air **14**: 175-183.

O'Neill, M.S., Jerrett, M., Kawachi, I., Levy, J.I., Cohen, A.J., Gouveia, N., Wilkinson, P., Fletcher, T., Cifuentes, L., Schwartz, J., 2003. Health, wealth, and air pollution: advancing theory and methods. Environ. Health Perspect. **111**, 1861–1870.

Ozkaynak, H., M. Zufall, J. Burke, J. Xue and J. Zidek (1999). A probabilistic population exposure model for PM10 and PM2.5. Epidemiology **10**(4): S79-S79.

Ozkaynak H., Xue J., Spenglr J., Wallace L., Pellizzari E. & Jenkins P. (1996) Personal exposure to airborne particles and metals: results from the particle TEAM Study in Riverside, California. J Expos Anal Environ Epidemiol **6**: 521-539

Owen, M.K., Ensor, D.S., & Sparks, L.E. (1992). Airborne particle sizes and sources found in indoor air. Atmos. Environ. Part A. **26**, 2149-2162.

Peters, A., D. W. Dockery, J. Heinrich and H. E. Wichmann (1997). Short-term effects of particulate air pollution on respiratory morbidity in asthmatic children. European Respiratory Journal **10**(4): 872-879.

Pope, C. A. (2000). Epidemiology of Fine Particulate Air Pollution and Human Health: Biological Mechanisms and Who's at Risk? Environmental Health Perspectives Supplement **108**(S4): 713-724.

Raaschou-Nielsen, O., O. Hertel, B. L. Thomsen and J. H. Olsen (2001). Air pollution from traffic at the residence of children with cancer. American Journal of Epidemiology **153**(5): 433-443.

Rea, A. W., M. J. Zufall, R. W. Williams, L. Sheldon and C. Howard-Reed (2001). The influence of human activity patterns on personal PM exposure: A comparative analysis of filter-based and continuous particle measurements. Journal of the Air & Waste Management Association **51**(9): 1271-1279.

Riain C., Mark, K., Davies, M., Harrision, R.M., and Byne, M.A(2003) Averaging periods for indoor–outdoor ratios of pollution in naturally ventilated non-domestic buildings near a busy road. Atmospheric Environment **37**: 4121-4132.

Rotko, T., Koistinen, K., Hanninen, O., Jantunen, M. (2000). Sociodemographic descriptors of personal exposure to fine particles (PM2.5) in EXPOLIS Helsinki. J. Expo. Anal. Environ. Epidemiol. **10**, 385–393.

Royal Bank of Canada (2007). Online rates and statistics. http://www.bankofcanada. ca/en/rates/exchform.html

Samet, J. M., F. Dominici, F. C. Curriero, I. Coursac and S. L. Zeger (2000). Fine particulate air pollution and mortality in 20 US Cities, 1987-1994. New England Journal of Medicine **343**(24): 1742-1749.

Setton, E., Hystad, P., Keller, P. (2005) Opportunities for Using Spatial Property Assessment Data in Air Pollution Exposure Assessments. International Journal of Health Geographics. **4**(26): 1-8.

Schwartz, J., D. W. Dockery and L. M. Neas (1996). Is daily mortality associated specifically with fine particles? Journal of the Air & Waste Management Association **46**(10): 927-939.

Spengler, J., L. Neas, S. Nakai, D. Dockery, F. Speizer, J. Ware and M. Raizenne (1994). "Respiratory Symptoms and Housing Characteristics." Indoor Air-International Journal of Indoor Air Quality and Climate **4**(2): 72-82.

Spengler, J.D., Dockery, D.W., Turner, W.A., Wolfson, J.M. and Ferris, B.G. Jr. (1981). Long-term measurements of respirable sulfates and particles inside and outsides homes. Atmos. Environment. **15**:23-30.

Sheldon, I.S., Hartwell, T.D., Cox, B.G., Sickles J.E., Pellizzari, E.D., Smith, M.L., Perritt, R.L., and Jones, S.M. (1989). An investigation of infiltration and indoor air quality. Final Report. NY State ERDA Contract No. 736-Con-BCS-85. New York State Energy Research and Development Authority. Albany, NY.

Sherman, M., and Dickerhoff, P. (1998) Air tightness of US Dwellings. Report conducted by Lawrence Berkley Laboratory's. DE-AC03-76SF00098.

Sherman, M.H., Matson, N.E. (2001). Air tightness of new houses in the US. Proceedings, 22nd Air Infiltration and Ventilation Proceedings.

Thatcher, T. L., M. M. Lunden, K. L. Revzan, R. G. Sextro and N. J. Brown (2003). A concentration rebound method for measuring particle penetration and deposition in the indoor environment. Aerosol Science and Technology **37**(11): 847-864.

Thatcher, T.L., & Layton, D.W. (1995). Deposition, resuspension and penetration of particles within a residence. Atmos. Environ. **29**, 1487-1497.

Thornburg, J., D. S. Ensor, C. E. Rodes, P. A. Lawless, L. E. Sparks and R. B. Mosley (2001). Penetration of particles into buildings and associated physical factors. Part I: Model development and computer simulations. Aerosol Science and Technology **34**(3): 284-296.

US EPA (Environmental Protection Agency) (1995). Exposure Factors Handbook. EPA Review Draft No. EPA/600/P-95/002A, office of Research & Development, U.S. Environmental Protection Agency, Washington, D.C.

US National Research Council (2001). Research Priorities for Airborne Particulate Matter: III. Early Research Progress. US EPA ISBN-13: 978-0-309-07337-0.

Wallace, L. (1996). Indoor particles: A review. Journal of the Air & Waste Management Association **46**(2): 98-126.

Wallace, L. and R. Williams (2005). Use of personal-indoor-outdoor sulfur concentrations to estimate the infiltration factor and outdoor exposure factor for individual homes and persons. Environmental Science & Technology **39**(6): 1707-1714.

Wallace, L. A., H. Mitchell, G. T. O'Connor, L. Neas, M. Lippmann, M. Kattan, J. Koenig, J. W. Stout, B. J. Vaughn, D. Wallace, M. Walter, K. Adams and L. J. S. Liu (2003). Particle concentrations in inner-city homes of children with asthma: The effect of smoking, cooking, and outdoor pollution. Environmental Health Perspectives **111**(9): 1265-1272.

Watson, J.M., Scarinci, I.C., Klesges, R.C., Murray, D.M., VanderWeg, M., DeBon, M., Eck-Clemens, L.H., Slawson, D.L., McClanahan, B., (2003) Relationships among smoking status, ethnicity, socioeconomic indicators, and lifestyle variables in a biracial sample of women. Prev. Med. **37**, 138–147.

White, W. H. and H. H. Suh (2003). Monitoring exposure to ambient air pollutants. Journal of Toxicology and Environmental Health-Part A **66**(16-19): 1879-1882.

Wichmann, H. E. and A. Peters (2000). Epidemiological evidence of the effects of ultrafine particle exposure. Philosophical Transactions of the Royal Society of London Series a-Mathematical Physical and Engineering Sciences **358**(1775): 2751-2768.

Williams, F. L. R. and S. A. Ogston (2002). Identifying populations at risk from environmental contamination from point sources. Occupational and Environmental Medicine **59**(1): 2-8.

Yocom, J.E. (1982). Indoor – outdoor air quality relationships. J. Air Pollution Control Ass**. 32**, 500- 520.

Zeka, A., A. Zanobetti and J. Schwartz (2005). Short term effects of particulate matter on cause specific mortality: effects of lags and modification by city characteristics. Occupational and Environmental Medicine **62**(10): 718-725.

Appendix 1 – Ethics Waivers

Human Research Ethics Board
Office of Research Services
University of Victoria
Room A240 University Centre
Tel (250) 472-4545 Fax (250) 721-8960
Email ovprhe@uvic.ca Web www.research.uvic.ca

University of Victoria

Human Research Ethics Board
Certificate of Approval of Waiver

Principal Investigator	Department/School	Supervisor
Perry Hysted Graduate Student	GEOG	Dr. Peter Keller

Co-Investigator(s):

Dr. Peter Keller, Lead Investigator, GEOG
Ms. Eleanor Setton, Project Manager, GEOG

Project Title: **Infiltration Modeling in Support of Air Pollution Exposure Assessments**

Protocol No.	Approval Date	Start Date	End Date
05-239	22-Sep-05	22-Sep-05	21-Sep-06

Certification

This certifies that the UVic Human Research Ethics Board has examined this research protocol and concludes that, in all respects, the proposed research meets appropriate standards of ethics as outlined by the University of Victoria Research Regulations Involving Human Subjects.

Dr. Richard Keeler
Associate Vice-President, Research

This Certificate of Approval is valid for the above term provided there is no change in the procedures. Extensions or minor amendments may be granted upon receipt of a "Research Status" form.

05-239 Hysted, Perry

Human Research Ethics Board
Office of Research Services
University of Victoria
Room A240 University Centre
Tel (250) 472-4545 Fax (250) 721-8960
Email ovprhe@uvic.ca Web www.research.uvic.ca

University of Victoria

Human Research Ethics Board
Certificate of Approval of Waiver

Principal Investigator	Department/School	Supervisor
Perry Hysted Graduate Student	GEOG	Dr. Peter Keller

Co-Investigator(s):

Dr. Peter Keller, Lead Investigator, GEOG
Ms. Eleanor Setton, Project Manager, GEOG

Project Title: **Infiltration Modeling in Support of Air Pollution Exposure Assessments**

Protocol No.	Approval Date	Start Date	End Date
05-239	22-Sep-05	22-Sep-05	21-Sep-06

Certification

This certifies that the UVic Human Research Ethics Board has examined this research protocol and concludes that, in all respects, the proposed research meets appropriate standards of ethics as outlined by the University of Victoria Research Regulations Involving Human Subjects.

Dr. Richard Keeler
Associate Vice-President, Research

This Certificate of Approval is valid for the above term provided there is no change in the procedures. Extensions or minor amendments may be granted upon receipt of a "Research Status" form.

05-239 Hysted, Perry

Appendix 2 – Consent Form

LETTER OF CONSENT

Infiltration Modeling in Support of Air Pollution Exposure Assessments

You are being invited to participate in a study entitled "Infiltration Modeling in Support of Air Pollution Exposure Assessments", conducted by Perry Hystad, a masters student at the University of Victoria. You may contact him if you have further questions at (250) 472-4624 or by email at phystad@uvic.ca. This research is part a Masters Thesis conducted under the supervision of Dr. C. Peter Keller, who can be contacted at (250) 472-5058 or by email at pkeller@uvic.ca.

The objective of this research is to identify indoor levels of air pollution ($PM_{2.5}$), a key component of total personal exposure to air pollution, and model these levels using building characteristics, meteorology, topography, and ambient $PM_{2.5}$ measurements. Property assessment data (a GIS data source created for property taxation purposes) provides substantial information about building characteristics that can be used to model average indoor $PM_{2.5}$ levels at the region scale. The specific aim of this study is to develop a regression model that predicts indoor ambient $PM_{2.5}$ levels using ambient $PM_{2.5}$ levels and specific building characteristics.

Should you agree to participate in this research, your residence will be monitored for five days both in the heating and non-heating seasons. You will also be required to complete a time activity diary during each of these days, which will require approximately ten minutes each day.

Your participation in this research is completely voluntary. If you decide to participate, you may withdraw at any time without any consequences or any explanation. If you do withdraw from the study during a monitoring session, your data will be destroyed and will not be included in the results of the study. If you withdraw after completing a five day monitoring session that data will be included in the study. There are no known or anticipated risks to you by participating in this research.

Your confidentiality and the confidentiality of the data will be protected. All data will be stored and analyzed within the Spatial Sciences Laboratory at the University of Victoria. Paper records will be destroyed upon project completion (spring 2007), and digital files will continue to be stored within the secure UVIC Spatial Sciences Laboratory. Your anonymity will be protected, and any results of the research will not include personal or residential identifiers.

The development of a regional infiltration model has the potential to change the way in which exposure, population health, and epidemiology studies are conducted. Because people spend the majority of their time indoors, and are located in different types of buildings, the differences in total personal exposures between individuals represented by the same outdoor pollution concentrations (the current method of exposure classification) may be substantial. This research will help determine these differences, as well as how building characteristics affect pollution infiltration, and how future total exposure estimates can be improved. Enhanced estimates of exposure will help decrease exposure misclassification in health studies, further identify high-risk populations, and lead to better control and mitigation policies for air pollution.

It is anticipated that the aggregated results from this study will be shared with others. The results will form the foundation of a Masters Thesis and may be published and presented at research conferences. Data will also be used by other researchers in a population based air pollution model.

In addition to being able to contact the researcher and supervisor at the above phone numbers, you may verify the ethical approval of this study, or raise any concerns you might have, by contacting the Associate Vice-President, Research at the University of Victoria (250 472-4545).

Your signature below indicates that you understand the above conditions of participation in this study and that you have had the opportunity to have your questions answered by the researchers.

Name of Participant	*Signature*	*Date*

Appendix 3 – Activity Logs

Time	# People In Home	Sleeping	Cooking *	Window Open**	Cleaning ***	Burning ****		Notes
5:00-5:30 AM							F	
5:30-6:00 AM							F	
6:00-6:30 AM							F	
6:30-7:00 AM							F	
7:00-7:30 AM							F	
7:30-8:00 AM							F	
8:00-8:30 AM							F	
8:30-9:00 AM							F	
9:00-9:30 AM							F	
9:30-10:00 AM							F	
10:00-10:30 AM							F	
10:30-11:00 AM							F	
11:00-11:30 AM							F	
11:30-12:00 AM							F	
12:00-12:30 PM							F	
12:30-1:00 PM							F	
1:00-1:30 PM							F	
1:30-2:00 PM							F	
2:00-2:30 PM							F	
2:30-3:00 PM							F	
3:00-3:30 PM							F	
3:30-4:00 PM							F	
4:00-4:30 PM							F	
4:30-5:00 PM							F	
5:00-5:30 PM							F	
5:30-6:00 PM							F	
6:00-6:30 PM							F	
6:30-:7:00 PM							F	
7:00-7:30 PM							F	
7:30-8:00 PM							F	
8:00-8:30 PM							F	
8:30-9:00 PM							F	
9:00-9:30 PM [a]							F	
9:30-10:00 PM							F	
10:00-10:30PM							F	
2:00-2:30 AM							F	
2:30-3:00 AM							F	
3:00-3:30 AM							F	
3:30-4:00 AM							F	
4:00-4:30 AM							F	
4:30-5:00 AM							F	

[a] Time periods removed to fit on one page.
* Please note type of cooking, for example: baking, frying, etc.
** Please note the location and width of opening for each window open.
*** Cleaning refers to vacuuming, dusting, and sweeping only.
**** Please note when candles and incense are burning in home. Circle “F” if fireplace is being used and note type.

Appendix 4 – Residential Survey

Residential Information form:

Date: ______________________________ ID#: ______

Address: ______________________________

____

Q.1 Please record the following characteristics of your residence:

Year built		Basement	
Years Improved		Finished Basement	
# of Stories		Partially Finished B.	
# of Rooms		Main Ceiling height	
# of Bedrooms		Sq. footage	
Wood Fireplaces		# of Windows	
Gas Fireplaces		# Storm Windows	
Primary Heating		# Double P. Windows	
Cooking Stove Types			

Q.2 Does the house have an Air Conditioning system?

- ❑ Yes
- ❑ No

If Yes, what type?

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

Q.3 Number of windows that open in home (percentage)

- ❑ None
- ❑ Approximately 25%
- ❑ Approximately 50%
- ❑ Approximately 75%
- ❑ All

Q.4 Are windows left open while you are sleeping?

- ❑ Yes (how many and in what rooms?) ______________________________
- ❑ No

Q.5 How often are other windows opened for cooling/ventilation purposes?

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

Q.6 Estimated percentage of floor space covered with carpets (for the entire house):

- ❑ None
- ❑ < 25%
- ❑ 25 – 50%
- ❑ 50 – 75%
- ❑ > 75%

Q.7 Do you have any indoor pets?

- ❑ Yes (How many and what types?) ____
- ❑ No

Q.8 Does your stove have a Ventilation fan or Range hood?

- ❑ Yes (Does it vent outside or is it re-circulated?) ______________________________
- ❑ No

If yes, how often is the Range Hood used when cooking?

- ❑ Never
- ❑ < 25%
- ❑ 25 – 50%
- ❑ 50 – 75%
- ❑ > 75%
- ❑ Always

Q.9 Does the house have a fireplace or woodstove?

- ❑ Yes
- ❑ No

If yes:

a. How many Wood Fireplaces/stoves? ______________________________________
b. How often is the Wood Fireplace/stove used? _______________________________
c. How many Gas Fireplaces? ____
d. How often is the Gas Fireplace used? ____________________________________

Q.10 Does the house have an independent air filter?

❑ Yes
❑ No

If yes,

a. What type? ______________________________
b. How often is it used? ________________________
c. Where is it located? ________________________

Q.11 Does the house have an HVAC (ventilation or air circulation) system?

❑ Yes
❑ No

If yes,

a. What type? ______________________________
b. How often is it used? ________________________

Q.12 Please list the individuals living in this household and their age and occupation.

Individual	Gender	Ethnicity	Age	Occupation
1				
2				
3				
4				
5				
6				

Q.13 Do you rent or own this home?

❑ Rent (What is your approximate monthly rent? ________________)
❑ Own

Q.14 Please indicate your approximate annual <u>household</u> income?

❑ <30,000
❑ 30,001 – 60,000
❑ 60,001 – 90,000
❑ 90,001 – 120,000
❑ 120,001 – 150,000
❑ 150,001 – 180,000
❑ >180,000

Q.15 Are there any other factors that you feel may impact the amount of outdoor air pollution inside your home or generated indoor levels of air pollution?

Apartment location in building (if applicable):

Q.16 Floor number: ____________

Q.17 Corner unit?

- ❑ Yes
- ❑ No

Q.18 Side of building?

❑ North ❑ South ❑ East ❑ West

Appendix 5 – Nephelometer calibrations

Monitor	Paired r^2	Adjustment to UVIC1
Jan. 25th		
UBC1	r^2=0.980	-
UBC2		= -4.77e-06 + 0.997(UBC2)
Feb. 5th		
UBC1	r^2=0.960	= 1.982e-06 +0.920(UBC1)
UBC2		= -2.83e-06 + 0.860(UBC2)
UVIC1	r^2=0.960	-
UVIC2		= 3.154e-06 + 0.969(UVIC2)
Feb. 17th		
UVIC1	r^2=0.985	-
UVIC2		= 2.572e-06 + 1.092(UVIC2)
March 10th		
UBC1	r^2=0.870	= -1.999e-6 +1.017(UBC1)
UBC2		= 3.268e-9 + 0.982(UBC2)
UVIC1	r^2=0.947	-
UVIC2		= 1.179e-06 + 0.982(UVIC2)
March 29th		
UBC1	r^2=0.999	= 9.305e-07 + 1.129(UBC1)
UBC2		= 9.305e-07 + 1.013(UBC2)
UVIC1	r^2=0.999	-
UVIC2		= 1.045e-06 + 1.019(UVIC2)
May 10th		
UBC1	r^2=0.830	= -4.610e-06 + 0.826(UBC1)
UBC2		= 3.676e-06 - 1.024(UBC2)
UVIC1	r^2=0.950	-
UVIC2		= 4.61e-06+1.024*(7.20e-06+0.895*(UVIC2)
July 5th		
UBC1	r^2=0.998	= 2.869e-05 + 1.060(UBC1)
UBC2		= 1.323e-05 + 0.876(UBC2)
UVIC1	r^2=0.999	-
UVIC2		= 2.967e-06 + 0.928(UVIC2)
August 14th		
UBC1	r^2=0.978	= 3.147e-05 + 0.849(UBC1)
UBC2		= 1.327e-05 + 1.436(UBC2)
UVIC1	r^2=0.996	-
UVIC2		= 4.270e-06 + 0.849(UVIC2)
August 20th		
UBC1	0.995	-8.747e-06 + 0.977(UBC1)
UBC2		1.629e-06 + 0.831(UBC1)
UVIC1	0.996	-
UVIC2		4.699e-7 +0.8518(UVIC2)
Sept. 20th		
UVIC1	r^2=0.990	-
UVIC2		1.9527e-6 + 0.8052(UVIC2)
October 26th		
UBC1	r^2=0.989	= -4.460e-06 +1.2017(UBC1)
UBC2		= 1.605e-06 + 0.962(UBC2)
UVIC1	r^2=0.992	= -1.058e-06 + 1.202(UVIC1)

Monitor	Paired r^2	Adjustment to UVIC1
Nov. 25th		
UVIC1	r^2=0.980	-
UVIC2		4.203e-06 + 0.827(UVIC2)
Dec. 7th		
UBC1	r^2=0.982	-1.661e-05 + 1.206(UBC1)
Mobile1		-

*Adjusted to UVic2 due to baseline shift of Uvic1.

Appendix 6 – Quality control criteria (Relationship between I/O data during non-source periods (23:00 to 6:00). Highlighted events do not meet QC criteria.

House ID	Monitor Start Date	Significance (Indoor/outdoor)	Median Ratio (indoor/outdoor)
1	1/9/2006	0.000	0.447
2	1/15/2006	0.000	1.030
3	1/19/2006	0.000	0.488
4	1/26/2006	0.445	1.511
5	1/26/2006	0.000	1.030
6	1/30/2006	0.000	0.425
7	2/5/2006	0.000	0.583
8	2/5/2006	0.000	0.855
9	2/10/2006	0.000	0.752
10	2/10/2006	0.000	0.515
11	2/17/2006	0.000	0.550
12	2/18/2006	0.000	0.622
13	2/22/2006	0.008	0.557
14	2/25/2006	0.000	0.479
15	3/7/2006	0.000	0.232
16	3/2/2006	0.000	0.699
17	3/11/2006	0.000	0.234
18	3/12/2006	0.000	0.891
19	3/17/2006	0.387	0.648
20	3/19/2006	0.000	8.190
21	3/22/2006	0.853	0.710
22	3/24/2006	0.000	0.915
23	4/3/2006	0.000	0.835
24	4/12/2006	0.088	0.409
25	4/11/2006	0.000	0.869
26	4/8/2006	0.055	1.386
27	4/12/2006	0.000	0.510
28	4/18/2006	0.000	0.799
29	4/27/2006	0.000	0.610
30	4/27/2006	0.000	1.000
31	12/10/2006	0.108	0.520
32	5/2/2006	0.000	0.589
33	5/13/2006	0.010	0.694
34	5/17/2006	0.000	0.414
35	5/18/2006	0.000	0.335
36	6/7/2006	0.000	0.837
37	6/7/2006	0.000	0.488
38	6/14/2006	0.000	0.205
39	7/17/2006	0.000	0.924
40	8/28/2006	0.000	0.536
1B	6/12/2006	0.000	0.934

House ID	Monitor Start Date	Significance (Indoor/outdoor)	Median Ratio (indoor/outdoor)
2B	6/25/2006	0.000	0.433
3B	6/29/2006	0.000	0.474
5B	6/19/2006	0.002	0.655
6B	6/24/2006	0.000	0.910
7B	7/12/2006	0.000	0.849
8B	9/19/2006	0.000	0.890
9B	7/28/2006	0.000	1.432
10B	10/11/2006	0.000	0.783
11B	9/12/2006	0.000	0.682
12B	8/2/2006	0.026	0.878
13B	11/1/2006	0.000	0.884
14B	8/8/2006	0.000	0.894
15B	9/24/2006	0.000	0.783
16B	11/1/2006	0.000	1.237
17B	9/22/2006	0.000	0.816
19B	5/3/2006	0.029	0.871
20B	10/4/2006	0.000	0.935
21B	9/27/2006	0.000	0.550
22B	10/27/2006	0.000	1.303
23B	12/4/2006	0.000	0.482
24B	10/3/2006	0.606	0.954
25B	10/20/2006	0.000	0.690
27B	10/27/2006	0.000	0.719
28B	10/10/2006	0.000	0.745
29B	11/7/2006	0.000	0.218
30B	11/20/2006	0.000	0.859
32B	9/29/2006	0.703	1.158
33B	12/4/2006	0.000	0.302
34B	10/20/2006	0.000	0.934
35B	11/8/2006	0.000	2.177
36B	11/13/2006	0.000	0.761
37B	11/28/2006	0.000	0.644
38B	10/15/2006	0.001	0.910
39B	10/15/2006	0.689	2.130

Appendix 7 – CRD indoor and outdoor monitoring data summary

ID	Finf	Mean In	Mean Out	Med. In	Med. Out	SD In	SD Out	90th In	90th Out
1	0.51	1.65	3.57	1.05	2.72	1.92	2.88	3.55	7.16
2	1.17	7.09	6.13	4.34	4.78	10.04	5.12	11.59	13.66
3	0.73	6.00	12.25	5.18	7.39	3.27	12.56	11.33	36.41
4	1.00	6.87	5.52	6.56	5.23	2.95	1.98	10.45	8.25
5	0.34	8.86	4.50	6.48	3.48	8.79	3.24	19.51	9.05
6	0.47	4.16	5.15	2.45	4.13	5.03	2.94	8.49	9.06
7	0.62	6.10	10.07	4.90	5.79	3.80	10.99	13.16	27.41
8	0.47	7.06	9.28	4.96	6.02	6.49	9.58	15.90	20.46
9	0.23	9.34	12.83	5.51	5.80	8.70	16.31	22.37	31.29
10	0.45	8.36	17.99	5.36	10.40	10.52	17.84	14.68	42.90
11	0.33	11.28	12.86	7.89	11.21	20.78	10.29	15.71	23.90
12	0.31	5.66	7.88	3.82	4.92	12.27	7.52	5.97	18.45
13	0.44	5.55	10.25	3.95	7.61	5.90	8.02	9.23	21.62
14	0.22	4.80	5.99	3.03	5.71	12.25	2.43	4.77	9.25
15	0.68	3.98	10.64	1.93	8.32	5.98	6.98	7.76	17.68
16	0.30	5.90	5.04	2.99	3.82	13.97	4.15	9.02	9.35
17	0.71	2.96	9.38	1.92	6.34	3.40	7.68	7.46	21.04
18	0.39	7.02	6.96	5.86	5.66	4.67	4.91	9.78	13.12
19	0.24	14.76	8.98	6.55	7.23	23.99	6.20	42.06	16.37
21	0.77	19.34	6.02	2.62	3.13	55.96	8.96	33.21	10.76
22	0.69	13.20	7.10	6.79	5.87	19.86	4.96	21.41	12.28
23	0.44	17.49	12.94	8.42	10.15	30.26	13.12	22.66	23.16
24	0.75	5.42	8.13	3.96	7.51	6.72	2.55	7.38	11.06
25	0.90	9.92	9.37	8.95	9.06	4.57	4.67	15.65	15.66
26	0.65	11.18	6.76	8.78	5.10	12.24	4.15	18.12	12.65
27	0.63	11.55	8.24	7.44	7.23	13.60	2.80	20.65	12.48
28	0.56	7.92	9.14	6.05	7.08	8.36	6.59	11.02	16.21
29	0.95	7.12	7.89	6.62	7.03	3.08	3.81	11.25	14.29
30	0.43	8.25	7.06	7.32	6.17	4.77	4.29	11.58	13.15
31	0.61	5.84	8.78	3.98	7.96	8.68	3.80	8.67	13.95
32	0.52	5.12	6.63	4.46	6.20	4.99	2.18	7.19	9.81
33	0.50	6.53	7.57	6.57	7.13	2.00	2.98	9.08	11.69
34	0.38	3.64	4.60	2.75	4.26	4.37	2.53	6.30	7.43
35	0.91	3.75	8.65	3.39	8.28	2.47	2.65	6.11	12.56
36	0.57	10.52	9.05	8.94	8.34	10.06	3.17	14.69	13.73
37	0.54	6.80	8.63	4.40	7.79	17.22	2.34	7.56	12.66
38	0.99	2.92	4.22	2.16	3.60	3.29	2.11	5.55	7.05
39	0.59	6.56	5.59	6.09	4.83	2.82	2.75	9.66	9.97
40	0.70	5.58	6.41	5.27	5.02	4.86	5.32	11.11	13.39
1b	0.59	2.77	3.03	2.48	2.46	1.49	2.22	4.73	5.91
2b	0.57	6.14	9.99	6.45	8.12	3.81	5.29	12.00	18.08
3b	0.84	5.98	8.91	5.37	8.11	2.66	3.42	9.00	13.97

ID	Finf	Mean In	Mean Out	Med. In	Med. Out	SD In	SD Out	90th In	90th Out
5b	0.99	3.25	2.95	2.93	2.70	3.31	1.51	4.11	4.34
6b	0.95	5.25	4.99	4.82	4.46	2.38	2.09	8.39	7.77
7b	0.79	2.76	2.38	2.49	1.99	1.96	1.97	3.96	3.89
8b	1.00	9.36	7.37	6.17	5.23	9.64	4.70	17.23	14.55
9b	0.49	3.64	2.31	2.95	2.02	1.96	1.28	6.40	4.25
10b	0.70	10.58	15.86	9.87	13.40	6.14	12.35	19.14	34.41
11b	1.00	4.56	2.92	2.82	2.85	5.70	0.96	9.01	3.97
12b	0.56	5.22	4.40	4.68	4.12	2.91	1.28	7.26	6.19
13b	0.90	6.94	9.69	4.86	5.69	5.25	9.31	13.51	23.41
14b	0.87	5.34	4.94	4.76	4.26	3.05	2.18	9.01	8.77
15b	0.80	7.95	8.22	7.15	8.06	2.97	3.38	12.06	13.34
16b	0.72	13.01	8.28	9.86	6.26	12.92	6.23	20.54	18.67
17b	0.71	4.16	5.37	3.93	4.84	1.64	2.62	6.08	7.93
19b	0.86	13.06	8.51	8.06	8.10	15.55	2.57	26.21	11.38
20b	0.57	8.33	7.01	7.08	6.76	4.56	2.76	12.05	11.05
21b	0.71	3.86	4.98	3.47	4.15	2.91	4.01	6.79	7.47
22b	0.30	13.51	11.38	10.01	9.82	14.40	7.91	22.91	23.78
23b	0.44	7.93	19.06	6.55	17.06	4.05	10.29	14.38	33.08
24b	0.52	18.54	6.02	7.92	5.42	33.57	2.24	35.41	9.12
25b	0.54	11.25	13.24	9.61	12.96	7.01	5.57	16.69	21.56
27b	0.49	10.31	13.07	8.87	11.54	6.86	11.16	20.18	23.44
28b	0.15	11.11	13.94	7.12	10.88	13.14	9.05	17.57	27.96
29b	0.66	5.54	13.06	3.97	10.61	5.07	8.79	12.22	26.70
30b	0.84	5.62	5.83	4.10	4.18	6.72	5.06	11.13	9.92
32b	0.29	11.96	4.75	6.11	4.45	35.54	2.43	13.48	8.03
33b	0.71	6.10	17.78	5.55	16.89	3.08	5.62	9.07	24.80
34b	1.00	12.95	12.98	12.21	12.78	6.63	5.06	22.50	20.31
35b	0.70	12.55	8.96	10.88	5.59	6.31	8.86	16.69	17.79
36b	0.53	7.26	9.42	6.69	7.62	2.92	6.11	11.37	15.26
37b	0.70	8.21	12.68	7.06	10.38	3.90	6.79	14.06	22.44
38b	0.51	15.58	14.68	12.92	13.37	11.78	7.98	24.15	28.87