Development and assessment of a physics-based simulation model to investigate residential PM_{2.5} infiltration across the US housing stock

Authors: Logue, J.M.¹; Sherman, M.H.¹; Lunden, M.M.²; Klepeis, N.E.^{3,4}; Williams, R.⁵, Croghan, C.⁵, Singer, B.C.¹

¹Energy Technologies Area, Lawrence Berkeley National Laboratory, Berkeley, California, USA

²Aclima Inc., San Francisco, CA, USA;

³Department of Civil and Environmental Engineering, Stanford University, Stanford, California, USA;

⁴Center for Behavioral Epidemiology and Community Health (C-BEACH), Graduate School of Public Health, San Diego State University Research Foundation, San Diego State University, San Diego, California, USA

⁵ Human Exposure and Atmospheric Sciences Division, US Environmental Protection Agency, Triangle Research Park, NC, USA

Corresponding author: Logue, J.M.; jmlogue@lbl.gov

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ABSTRACT

The Lawrence Berkeley National Laboratory Population Impact Assessment Modeling Framework (PIAMF) was expanded to enable determination of indoor PM_{2.5} concentrations and exposures in a set of 50,000 homes representing the US housing stock. A mass-balance model is used to calculate time-dependent pollutant concentrations within each home. The model includes size- and species-dependent removal mechanisms. The particle model was applied to the housing samples of the Relationship of Indoor, Outdoor, and Personal Air (RIOPA) and The Detroit Exposure and Aerosol Research Study (DEARS) studies to compare model- and measurement-based estimates of indoor PM_{2.5} of outdoor origin. Model-derived distributions of infiltration factors (ratio of indoor PM_{2.5} of outdoor origin to outdoor PM_{2.5}) are compared to measurement-based distributions obtained in studies conducted in 11 US cities.

INTRODUCTION

Ambient fine particulate matter (PM_{2.5}) mass concentration varies in magnitude, chemical composition, and particle size distribution as sources, atmospheric formation and ageing, and removal processes vary. Spatial variations occur over large regions and sources vary from urban to rural areas within regions. Temporal variations occur over diurnal, weekly, and seasonal scales.

Elevated concentrations of PM_{2.5} in the atmosphere have been associated with increased morbidity and mortality in the population (Pope et al. 2009). While most epidemiological studies have examined relationships between health outcomes and measured ambient PM_{2.5} concentrations (McCormack et al. 2009), exposure to outdoor PM_{2.5} predominantly occurs indoors (Meng et al. 2005). Indoor sources also contribute significantly to PM_{2.5} exposures and the majority of indoor PM_{2.5} exposure occurs in residences (VanRyswyk et al. 2013). US residents spend nearly 90% of their time indoors and almost 70% at home (Klepeis et al. 2001). Reducing PM_{2.5} exposures in US homes could provide an annual health benefit of \$50-150 billion (Logue et al. 2012).

A number of building factors influence the concentration and composition of PM_{2.5} indoors (Marsik and Johnson 2008; Prasauskas et al. 2014; Urso et al. 2015). Loss mechanisms include deposition as outdoor air infiltrates through the building envelope, deposition to indoor surfaces, and particle removal by filtration. Some particles can undergo chemical reactions indoors, which can lead to a net gain or loss (Lunden et al. 2003a; Lunden et al. 2008). Variability in home characteristics (e.g., air tightness, presence of air conditioning), operation (e.g., use of air conditioning and/or air filters, opening of windows), and occupant activities (e.g. cooking, candle burning) can result in substantial variability in outdoor PM_{2.5} exposure and intake in homes that experience similar outdoor concentration profiles (Meng et al. 2012; Isaacs et al. 2013). Diurnal and seasonal variability in outdoor PM_{2.5} and the atmospheric conditions (temperature, wind, pressure, etc.) that drive infiltration-based air exchange cause temporal variability in PM_{2.5} infiltration, affecting in-home exposures.

The Population Impact Assessment Modeling Framework (PIAMF) was developed to quantify the energy and health impacts of possible or actual changes to the U.S. housing

stock. The PIAMF applies physics-based simulation models to calculate one or more environmental or energy performance parameters for each home in a sample developed to represent one or more segments of the population. Results from the individual homes are compiled to provide the statistics for population impacts. The approach can be applied at varying temporal or spatial scales. Previous applications have assessed the energy impacts of range hood use (Logue and Singer 2013) and building tightening (Logue et al. 2013) for the United States housing stock and the exposure impacts of natural gas cooking in Southern California (Logue et al. 2014). The capability to track the introduction and removal of $PM_{2.5}$ into homes has been added to the PIAMF. The PIAMF can be used to assess how variations in outdoor $PM_{2.5}$, indoor sources, and housing and occupant parameters affect indoor $PM_{2.5}$ distributions across the population. This tool will allow for analysis of characteristics that are driving exposures across the US housing stock and the development of guidance for cost-effective methods to reduce exposure. Similar methods have been applied to the UK housing stock to assess indoor air quality (Das et al. 2014).

In the present work we (1) describe the $PM_{2.5}$ dynamics model that has been added to the PIAMF, and (2) compare PIAMF-derived and measurement-derived estimates of study cohort and regional air exchange rates and $PM_{2.5}$ infiltration factors. The $PM_{2.5}$ infiltration factor is the ratio of the indoor concentration of outdoor $PM_{2.5}$ to the outdoor concentration of $PM_{2.5}$.

METHODS

Overview

Figure 1 presents a graphical description of the current application of the PIAMF to predict particle concentrations in U.S. homes. The user selects operating conditions of modeled homes including season, and type and level of filtration. The $PM_{2.5}$ particle dynamics model (PDM) is applied to each home included in the PIAMF housing sample. The PDM executes the following three tasks. 1) It generates a typical week-long hourly outdoor particle concentration profile resolved by size and chemical composition for the season selected (fall, spring, summer, or winter) and location of the modeled home. 2) It calculates minutely airflows through the building envelope, windows, mechanical ventilation, HVAC ducts, and any auxiliary filtration systems. 3) It computes minutely indoor particle concentrations resolved by size and composition. The ultimate goal is to use the PIAMF framework to assess $PM_{2.5}$ exposures and control measures in the US housing stock. Future PIAMF applications will include indoor sources and occupant behavior. The model was developed with minutely resolution so that these factors can be characterized at sufficient resolution.

Figure 1. Graphical representation of PIAMF for particle modeling.

PIAMF housing sample

Previous PIAMF applications included the development of a representative housing sample for the US. Full details of the developed PIAMF housing sample can be found in Logue et al. (2013); a brief description is provided below.

Using data from the Residential Energy Consumption Survey (RECS) (US EIA 2009), we defined a sample of 50,877 homes that is weighted to represent the U.S. housing stock. Required housing parameters that are not available in the RECS – including normalized leakage of the building envelope, home size, and thermostat temperatures (available for some but not all RECS homes) – were estimated or assigned based on home characteristics that were specified in the RECS and relationships derived from the literature. As shown in Figure 1, the PM_{2.5} dynamic model is applied to each home or a subset of homes in the PIAMF housing sample when assessing PM_{2.5} exposures and controls. The results for each home are aggregated to estimate population impacts.

PM_{2.5} dynamic model: Calculating indoor concentrations

A single-zone mass balance model is applied to each home to estimate indoor PM_{2.5} concentrations. The model includes factors that affect particle transport and fate in the home including penetration, emissions, dilution, deposition, removal by filtration, chemical loss rates, and removal by air exchange. The model simulates particle dynamics by size and composition. The indoor air model uses the following governing mass-balance equation:

$$\overbrace{\text{Change in mass}}^1 = \overbrace{\text{Mass in}}^2 - \overbrace{\text{Mass out}}^3 \quad (1)$$

$$\frac{\overbrace{dC_{in,i,j}}^1}{dt} = \overbrace{\frac{E_{i,j}}{V} + (A_{win}P_{win,i} + A_{infiltr}P_{infiltr,i} + A_{mech}P_{mech,i})C_{out,i,j}}^2 - \overbrace{(k_{loss,i} + k_{evap,i,j} + A_{win} + A_{infiltr} + A_{mech} + RE_{HVAC,i}A_{HVAC} + RE_{recirc,i}A_{recirc})C_{in,i,j}}^3 \quad (2)$$

In Equation 2, the mass balance equation is normalized by house volume V . The symbol i is used to track processes by particle size bin and j refers to a specific chemical constituent of $PM_{2.5}$. Other symbols are used as follows: k_{loss} is a first order loss rate for deposition to indoor surfaces and is size-dependent; k_{evap} is the species dependent evaporative loss rate; C_{in} is the indoor concentration; C_{out} is the outdoor concentration; P is the particle penetration loss for the different ventilation processes that bring outdoor air indoors. The “ A ” terms represent the airflow (in air changes per hour, or ach) through the window (A_{win}), infiltration ($A_{infiltr}$), mechanically supplied air (A_{mech}), the central duct system (A_{HVAC}), and recirculation system (A_{recirc}). The online supplement describes the method for calculating these time-varying airflows. RE_{recirc} is the size-dependent particle removal efficiency for air flowing through any recirculating or in-room air-cleaning device and RE_{duct} is the removal efficiency of the central heating or cooling duct system and includes removal due to ducts and filters in the system. The parameter E is the mass emission rate of indoor sources. Indoor sources are not included in this study. We assume there is no reactivity between $PM_{2.5}$ components.

In order to simplify the presentation of the equations, we introduce two parameters which represent the household gain rate of $PM_{2.5}$ per unit outdoor concentration, G_i , and the loss rate of $PM_{2.5}$ per unit concentration indoors, $L_{i,j}$. Using these parameters, Equation 2 becomes:

$$\frac{\overbrace{dC_{in,i,j}}^1}{dt} = \overbrace{\frac{E_{i,j}}{V} + G_i C_{out,i,j}}^2 - \overbrace{L_{i,j} C_{in,i,j}}^3 \quad (3)$$

Equation 3 was adapted into Equations 4 and 5 to separately track indoor pollutants originating from indoor emissions ($C_{in_I,ij}$) and indoor pollutants from outdoor sources ($C_{in_O,ij}$).

$$\frac{\overbrace{dC_{in_I,ij}}^1}{dt} = \overbrace{\frac{E_{i,j}}{V}}^2 - \overbrace{L_{i,j} C_{in_I,ij}}^3 \quad (4)$$

$$\frac{\overbrace{dC_{in_O,ij}}^1}{dt} = \overbrace{G_i C_{out,i,j}}^2 - \overbrace{L_{i,j} C_{in_O,ij}}^3 \quad (5)$$

The total $PM_{2.5}$ concentration of indoor pollutants can be calculated by summing the contributions from indoor and outdoor sources:

$$C_{in}(t) = \sum_{i,j} [C_{in_I,ij}(t) + C_{in_O,ij}(t)] \quad (6)$$

This superposition approach was used by Klepeis (1999) to combine discrete source emissions in a residence. Equations 4 and 5 can each be solved recursively for $C_{in_I,ij}$ and $C_{in_O,ij}$, respectively, with any of the non-concentration parameters held constant within a

given time step and allowed to vary from one time step to another. Equations 7 and 8 present the recursive solutions for $C_{in_I,ij}$ and $C_{in_O,ij}$, respectively.

$$C_{in_I,ij}(t) = C_{in_I,ij}(t - \Delta t) \exp^{-(L_{ij}(t))\Delta t} + \frac{E_{ij}(t)(1 - \exp^{-(L_{ij}(t))\Delta t})}{(L_{ij}(t))V} \quad (7)$$

$$C_{in_O,ij}(t) = C_{in_O,ij}(t - \Delta t) \exp^{-(L_{ij}(t))\Delta t} + C_{out,ij}(t) \frac{G_i(t)(1 - \exp^{-(L_{ij}(t))\Delta t})}{(L_{ij}(t))} \quad (8)$$

In the current model application, the chemical components, denoted by j , are ammonium sulfate (AS), ammonium nitrate (AN), organic mass (OM), elemental carbon (EC), and “other” (O). The size bins, denoted by subscript i , are those measured by the MOUDI instrument (Chow et al. 2008) ($<0.1\mu\text{m}$, $0.1\text{--}0.18\mu\text{m}$, $0.18\text{--}0.32\mu\text{m}$, $0.32\text{--}0.56\mu\text{m}$, $0.56\text{--}1.0\mu\text{m}$, $1\text{--}1.8\mu\text{m}$, $1.8\text{--}2.5\mu\text{m}$) although the number and size of bins can be varied to accommodate data taken from other instruments.

One of the aims of the present work is to assess the model predictions of indoor concentrations due to outdoor $\text{PM}_{2.5}$, $C_{in_O,ij}$.

$\text{PM}_{2.5}$ dynamic model: Calculating outdoor concentrations ($C_{out,ij}$)

We combined several sources of measured $\text{PM}_{2.5}$ data to develop profiles of size- and chemically-resolved outdoor $\text{PM}_{2.5}$ concentrations that are also resolved by location, season, weekday/weekend, and hour of day. We aggregated available daily, hourly, and speciation data for 2009-2012 from the EPA AirData site (<http://www.epa.gov/airdata>) as well as available size distributions of select chemical species of $\text{PM}_{2.5}$ from the NASA NARSTO site (https://eosweb.larc.nasa.gov/project/narsto/epa_table). For each site, for each season, we determined the weekend/weekday mean values for daily $\text{PM}_{2.5}$, mean diurnal patterns of $\text{PM}_{2.5}$, and mean speciation mass based on available data. This size distribution data for AN, AS, OM, and EC came from outdoor monitoring conducted in Atlanta, Houston, and Pittsburgh as part of the Super Site initiative (Liu et al. 2003; Cabada et al. 2004). Size distributions for the “other” chemical class are taken from representative distributions by Seinfeld and Pandis (2006). Using the aggregated data from these sites, the PDM generates a weeklong, outdoor, hourly resolved profile of $\text{PM}_{2.5}$ mass divided into the 35 bins defined by chemical species and particle size for each modeled home for the season modeled (spring, summer, fall, or winter).

Based on the modeled homes location, the closest monitoring sites with $\text{PM}_{2.5}$ daily data, hourly data, speciation data, and size distribution data are selected (see Figure S2 in the online supplement). Previously determined mean values for those sites are used to develop a typical weekday (Monday through Friday) and weekend day (Saturday, Sunday) hourly profile during the season selected for the model run. The hourly profiles are converted to minutely profiles by assuming the same value for the minutes of a given hour. The four major steps used to develop outdoor concentration profiles from monitoring data are shown in Figure S3 in the online supplement and described here. 1) From the daily data we determine average outdoor concentration for weekends and weekdays. 2) The hourly data is used to develop diurnal profiles of the pattern of hourly concentrations relative to daily averages. The weekend and weekday non-dimensional diurnal profiles are multiplied by the weekend and weekday daily average concentrations to develop quantitative diurnal concentration profiles. 3) The weekend/weekday diurnal profiles are then separated into five diurnal profiles, one for each chemical species based on the closest speciation site data. 4) The average

weekend/weekday fraction of each chemical species mass in each particle size bin is determined from data from the closest monitoring site with size distribution data. Details of how speciation data are used are included in the online supplement.

PM_{2.5} dynamic model: Size and species dependent model parameters

Table 1 summarizes select size and species dependent model parameters for the PDM.

Deposition rates, k_{loss} , are a function of particle size distribution and home characteristics (Thatcher et al. 2002). Thatcher et al. (2003) and Long et al. (2001) measured size dependent deposition rates in homes in winter and summer. We developed distributions of expected k values for each of our defined particle size bins based on these studies. For each size bin, we determined the normal distribution that best fit the combined data from the two studies. The distributions reported by each study were weighted by the number of homes in the study. The result was a mean and standard deviation of the deposition rate distribution for each particle size bin. The shape of the deposition curve is determined by the physics of Brownian motion and inertial deposition. Sampling the deposition distributions for each size bin separately for each home could potentially result in a deposition / particle size relationship not supported by the physics. For this reason, we assume the shape of the curve determined by the mean deposition of each size remains constant and the curve moves up or down for each modeled home. For each home we selected the deposition rate for the largest size bin from a normal distribution with the assumed mean and standard deviation shown in Table 1 and adjusted all size bins by the same fractional change from the mean value for the size bin.

Particle penetration factors, P , depend on particle size, but it is not a very strong dependence for the particle size bins that are significant contributors to PM_{2.5} mass (Long et al. 2001; Chen and Zhao 2011). We assigned P as a function of how air enters the home. For air that is supplied through the windows, we assume that P is 1.0. When air infiltrates through the building envelope, we used the same approach as we did for the particle first order deposition loss rate using penetration data from Thatcher et al. (2003) and Long et al. (2001).

Lunden et al. (2003b; 2008) showed that EC and AS infiltration could be modeled effectively using penetration, deposition loss rate values, and the building air exchange rates. Lunden et al. (2003a) found that AN loss rates are higher than those expected just from deposition alone. We used the fit derived by Herring et al. (2007) of the Lunden et al. data to estimate the evaporative loss rate, $k_{i, evap}$, of AN as a function of home temperature and particle size. At each time step, surface area of the particles in each bin was determined based on mass and assumed particle diameter at the median of the size range. $k_{i, evap}$ was assigned to each bin so that $k_{PM2.5, evap}$ was equal to that calculated for each time step as a function of temperature and so the $k_{i, evap}$ for each bin was linearly correlated with bin surface area. Higher OM (both gas and particle phase) indoors due to indoor sources can lead to increases in chemical partitioning to the particle phase as both organic particles and organic gases enter the home. Conversely, lower levels of OM indoors due to loss mechanisms and a lack of indoor sources leads to increases in chemical partitioning to the gas phase as outdoor air moves indoors. Temperature differences between indoors and outdoors also result in shifting to the gas phase or vice versa. Hodas and Turpin (2014) estimated the impact of these changes using data from the Relationship of Indoor, Outdoor, and Personal Air (RIOPA) Study (Weisel et al. 2005) and found that indoor concentrations of organic particles showed increases and decreases relative to those predicted assuming infiltration of conserved species (species assumed to have no loss mechanisms except dilution by ventilation) based on home operating conditions. The vast majority of homes had a change (increase or decrease) in the indoor concentration of outdoor-origin organic particles of less than 2 $\mu\text{g}/\text{m}^3$ compared to the modeled indoor

concentration using penetration, deposition, and air exchange rate based gains and losses only. These results indicate that the impact of outdoor organic particles on indoor organic particle concentrations is a function of home operating conditions and not just home location and characteristics. For our modeling efforts we have treated OM as a conserved species. This will overestimate OM concentrations in homes with no indoor sources and underestimate concentrations in homes with large OM sources.

To model the indoor PM_{2.5} for homes with ducted HVAC systems, we incorporated loss rates framed as the percentage of particles captured by a single pass through the duct system. Duct removal rates were taken for home HVAC system efficiencies measured by Stephens and Siegel (2012; 2013). There are no data for the 0.1–0.3 μm size range, which encompasses most of two of our seven modeled size bins (0.1–0.18 μm bin and 0.18–0.32 μm bin). For those bins we assumed the same duct single pass removal percentage (5%) as for the smallest modeled bin (<0.1 μm). While this may be a slight over-estimate of the actual rate for accumulation mode particles, any error has a small impact on the fraction of particles that pass through without capture. Table 1 summarizes select model parameters.

Table 1 Parameter values for PM_{2.5} dynamic model. Additional parameters are characterized in the online supplement in Table S1.

Parameters	Values
<i>Size bin, i</i>	Size bins: <0.1 μm , 0.1-0.18 μm , 0.18-0.32 μm , 0.32-0.56 μm , 0.56-1.0 μm , 1.0-1.8 μm , 1.8-2.5 μm
<i>Species, j</i>	AN=ammonium nitrate, AS=Ammonium sulfate, OM= organic mass, EC=elemental carbon, O= other
Penetration through open windows, $P_{i,\text{win}}$	Assumed to be 1 for all size bins.
Penetration via infiltration, $P_{i,\text{infiltr}}$	Selected for each home from a normal distribution with parameters noted (mean, standard deviation) for each size bin: <0.1 μm : (0.83, 0.08), 0.1-0.18 μm : (0.85, 0.07), 0.18-0.32 μm : (0.88, 0.05), 0.32-0.56 μm : (0.84, 0.05), 0.56-1.0 μm : (0.80, 0.08), 1.0-1.8 μm : (0.68, 0.04), 1.8-2.5 μm : (0.54, 0.10). Based on data in Thatcher et al (2003) and Long et al. (2001b).
$P_{i,\text{mech}}$	For this analysis, we assume no mechanical ventilation since there is relatively little in the existing housing sample. Values will be derived from manufacture specifications for future analyses.
Indoor deposition rate, $k_{i,\text{loss}}$	Selected for each home from a normal distribution with parameters noted (mean, standard deviation) for each size bin: <0.1 μm : (0.25, 0.06), 0.1-0.18 μm : (0.19, 0.04), 0.18-0.32 μm : (0.19, 0.03), 0.32-0.56 μm : (0.19, 0.04), 0.56-1.0 μm size bin: (0.29, 0.06), 1.0-1.8 μm : (0.45, 0.06), 1.8-2.5 μm : (0.60, 0.18). Based on data in Thatcher et al (2003) and Long et al. (2001b).
Evaporation rate, $k_{\text{evap},i,j}$	$k_{\text{PM}_{2.5},\text{evap}}$ was determined for each home for PM _{2.5} as a function of indoor temperature (Hering et al. 2007). $K_{i,\text{evap}}$ was determined for each size bin as a function of surface area.
Single pass loss rate in forced air duct, $RE_{i,\text{duct}}$	<0.1 μm size bin: 5%, 0.1-0.18 μm : 5%, 0.18-0.32 μm : 5%, 0.32-0.56 μm : 18%, 0.56-1.0 μm : 10%, 1.0-1.8 μm : 14%, 1.8-2.5 μm : 13% (Stephens and Siegel 2012; Stephens and Siegel 2013)
Single pass removal by filter in forced air system, $RE_{i,\text{recirc}}$	For this analysis, 0 for all homes. Values will be derived from manufacture specifications for future analyses.

Comparing modeled and measured data

Figure 2 illustrates the model-measurement comparisons we perform in the present work. We compare measured and modeled data in two ways: 1) by modeling air exchange (AER) and/or infiltration factors (F_{inf}) of specific measurement-study cohorts, groups of homes, using cohort-based inputs and 2) by modeling regional F_{inf} using PIAMF housing-stock inputs for specific cities where measurement data are available. In this work, we do not evaluate predictions of indoor concentrations directly, nor do we evaluate occupant $PM_{2.5}$ exposures.

The infiltration factor (F_{inf}) is a common metric used to represent the indoor concentration of outdoor $PM_{2.5}$. As shown in Equation 9, F_{inf} is the ratio of the time-averaged indoor concentration of outdoor particles to the time-averaged outdoor concentration.

$$F_{inf} = \left(\frac{\overline{c_{in}}}{\overline{c_{out}}} \right) = \frac{\left(\int_0^T c_{in,t} dt \right) / T}{\left(\int_0^T c_{out,t} dt \right) / T} \quad (9)$$

F_{inf} is an important metric because it allows for the use of central ambient monitoring data to estimate indoor concentrations of ambient $PM_{2.5}$.

The purpose of the first *cohort* comparison is to evaluate how well the PDM predicts AER and F_{inf} using input data from a well-defined set of homes. The purpose of the second comparison is to compare model predictions and measurements of F_{inf} distributions for entire regions, using the PIAMF housing sample inputs. Measurements have been conducted in select cities to estimate F_{inf} for use in exposure assessments. Measurement studies are limited in the number of homes they can measure due to cost constraints. The PIAMF's housing sample theoretically allows for modeling of all homes in a given region but may not capture all of the important home characteristics. The comparison will allow for assessment of how measurement and model derived F_{inf} distributions differ.

Cohort-Based Comparisons

The aim of the PIAMF approach is to capture central tendencies and distributional features of baseline conditions and interventions across the housing stock, not to accurately model the performance of each individual home. Assessment of PDM performance is thus done at the group, not the individual home level. For the present objective of assessing model performance of indoor concentrations of outdoor $PM_{2.5}$, we would ideally compare model predictions of indoor $PM_{2.5}$ to seasonally-defined, size- and species-resolved $PM_{2.5}$ measurements for large sample(s) of well-characterized, geographically dispersed homes with no indoor sources. We could then use the PDM to model the same groups of homes and compare the results. Unfortunately comprehensive datasets of this type do not exist.

Several exposure assessment studies have simultaneously measured indoor and outdoor $PM_{2.5}$ across urban and non-urban samples of homes (Williams et al. 2003; Rodes et al. 2010; Allen et al. 2012; Hsu et al. 2012; Habre et al. 2014b). These studies generally measured particle concentrations in operating homes with highly varying indoor source contributions to total indoor $PM_{2.5}$ and did not record sufficient information about the physical or operational characteristics of the homes to enable a meaningful comparison simulation with the PDM. We found two studies that had sufficient information to allow a meaningful comparison of results obtained with the PDM.

The Detroit Exposure and Aerosol Research Study (DEARS) and the Relationship of Indoor, Outdoor, and Personal Air (RIOPA) Study characterized sets of non-smoking homes in Detroit (DEARS); Los Angeles, CA (RIOPA); Houston, TX (RIOPA); and Elizabeth, NJ (RIOPA) (Weisel et al. 2005; Williams et al. 2009). Each home was studied over 2-5 day periods during which AER, $PM_{2.5}$ mass and $PM_{2.5}$ components were measured both indoors and outdoors. Although the homes were occupied, the measured values of $PM_{2.5}$ components that have negligible indoor sources can be used to calculate F_{inf} values for the study period. Despite the selection condition that no smoking occurred in study homes, DEARS reported that smoking actually occurred in 7.6% of the home measurement periods with potential impacts on concentrations of $PM_{2.5}$ mass and components. Both studies used continuous injection PFT tracers to measure AER. For the RIOPA study, $AER > 5.0$ ACH were removed from the dataset due to limit of detection concerns (Yamamoto et al. 2010). Both studies used x-ray fluorescence to measure the sulfur content of $PM_{2.5}$ and DEARS used ion chromatography and aqueous extraction to identify the nitrate content of $PM_{2.5}$. Both the RIOPA and DEARS studies selected homes exposed to a diverse set of potential outdoor pollutant sources. They are not representative samples of the housing stocks in the cities measured. In contrast, the PIAMF housing sample was developed to be a representative, weighted sample of the US housing stock.

We applied the PDM to the homes characterized in the DEARS and RIOPA datasets as shown in Figure 2A. For each measurement period in the homes, we compare modeled AER and F_{inf} distributions to those measured. We refer to the modeled groups of homes as DEARS and RIOPA cohorts to clarify that they are a different set than the representative housing sample derived from the RECS. Data needed to fully characterize each home for the model included all of the following: location at the county level, home type, building foundation for single family homes, size, number of stories, age, season of measurements, whether the home is low income, whether the home has heating or cooling ducts, and thermostat set points for indoor temperature. Not all homes had all of the necessary data. We assumed that homes were not low-income when no information was available. For all other parameters, when specific data was not available, we used the average value for the geographical area derived from the RECS database. Normalized leakage of the building envelope was assigned based on reported home characteristics using the algorithm developed by Chan et al(2013). We applied the PDM using 2 different approaches: 1) we used only the home characteristic data to model the homes using the PDM as specified in Figure 1; and 2) we used home characteristics, measured outdoor $PM_{2.5}$ concentration, and measured air exchange rate to estimate indoor concentrations. For the second approach we substituted the measured data for the PDM-derived estimates of the daily average outdoor $PM_{2.5}$ and AER described previously. Diurnal patterns were still derived from local monitoring sites. For the homes in these measurement studies, we do not know how much air entered through open windows/doors ($P=1$) versus through the building envelope ($P<1$). To explore sensitivity to this important variable, we ran the model using the measured AER in each home and assuming either (a) that all the airflow was through the open window or (b) that all the airflow was through the building envelope. These are bounding conditions for the effect of penetration pathway on indoor/outdoor ratios.

Based on the data available in the RIOPA and DEARS databases, we cannot directly calculate a $PM_{2.5} F_{inf}$ because the homes measured were occupied and likely had indoor sources. We are limited to comparing infiltration factors of modeled subcomponents of $PM_{2.5}$ to measured data. Both RIOPA and DEARS measured indoor and outdoor sulfur content of $PM_{2.5}$ and the DEARS study measured indoor/outdoor nitrate content of $PM_{2.5}$. As indoor sources of sulfur

are rare, and with the assumption that indoor loss mechanisms for the sulfur component of $PM_{2.5}$ are similar to those for infiltrated $PM_{2.5}$ as a whole, the ratio of measured indoor to outdoor sulfur content of $PM_{2.5}$ has been used to estimate F_{inf} (Sarnat et al. 2002; Allen et al. 2003; Wallace and Williams 2005; Allen et al. 2012; Habre et al. 2014b). Lunden et al. (2003a; 2008) and Hodas and Turpin (2014) have shown that not all components of $PM_{2.5}$ infiltrate in consistent proportions. The relative contributions of ammonium nitrate (AN) and organic matter (OM) to outdoor $PM_{2.5}$ and the strength of indoor OM sources will determine if F_{inf} values derived from sulfur or other conserved components of $PM_{2.5}$ overestimate or underestimate $PM_{2.5}$ infiltration. A large study in Edmonton, Canada found that F_{inf} estimates derived from ratios of sulfur measurements overestimated F_{inf} derived from high-time resolution indoor and outdoor PM_1 measurements (Kearney et al. 2014). For our assessment, we compared model-calculated, week-averaged, indoor/outdoor ratios of ammonium sulfate (AS) to measured indoor/outdoor ratios of $PM_{2.5}$ sulfur content. For the DEARS cohort we additionally compared model-calculated, week-averaged indoor/outdoor ratios of AN to indoor/outdoor measured ratios of $PM_{2.5}$ nitrate content. Not all homes included in the RIOPA and DEARS cohorts measured all components needed for inclusion in this analysis. Table 2 presents limited information on included homes. The homes were modeled for the season in which the measurements were taken and PDM results are the aggregated distributions of 15 repeated runs with all parameters assigned anew for each model execution (Logue et al. 2014). Presentation of results include both within and between home variability. For all model runs, the indoor concentrations were due to outdoor $PM_{2.5}$ and no indoor sources were included.

A) Cohort based comparison of measured and modeled AER and Infiltration Factor

B) Regional Comparison of Measured and Modeled Estimates of Infiltration Factor

Figure 2. Diagram of comparisons of measured and modeled data. A) Comparison of DEARS and RIOPA data sets to PDM model results using cohort inputs. B) Comparison of PIAMF regional F_{inf} predictions using stock inputs to regional F_{inf} estimates from measurement studies.

Table 2 Characteristics of modeled subset of RIOPA and DEARS cohorts with reported AER values or sufficient data to calculate F_{inf} . N indicates the number of multi-day home visits included. W/SP/S/F indicated the number of visits in winter/spring/summer/fall.

	Study	N (W/SP/S/F)	Opened Windows	Home Type			Relevant Data Measured
				House	Apt	O/U	
RIOPA:	(Weisel et al.	39	82%	69%	26%	5%	Sulfur, AER
California	2005)	(4/6/15/14)					
RIOPA:	(Weisel et al.	41	66%	34%	61%	5%	Sulfur, AER
New Jersey	2005)	(12/7/8/14)					
RIOPA:	(Weisel et al.	48	48%	48%	2%	50%*	Sulfur, AER
Texas	2005)	(15/14/8/11)					
DEARS:	(Williams et	206	Summer=79	87%	9.5%	3.5%	Sulfur, Nitrate, AER
Detroit	al. 2009)	(88/0/118/0)	%, Winter=3.4%				

*Predominately mobile homes. , NI=No Information, (w/sp/s/f)=winter/spring/summer/fall, Apt = apartment, O/U= other/unknown. Sulfur= indoor and outdoor sulfur content of PM2.5, Nitrate =indoor and outdoor nitrate content of PM2.5, AER= air exchange rate

Regional Comparisons

Measuring F_{inf} in homes is challenging because F_{inf} and AER vary over time for a given home based on weather and occupant behaviour (Kearney et al. 2014; Sherman et al. 2014). Studies that measured F_{inf} in homes have predominately done so over the course of one to a few days and report the ratio of the time-average indoor/outdoor concentration. This value may represent the average behaviour of the home, but may also represent an unusual condition. A measurement event is a snapshot. In addition to variability in a single home over time, there is variability within the housing stock that can affect infiltration. Homes chosen for F_{inf} measurements may not represent the population of homes in the specified geographical area. Homes are chosen in a given city, limiting the included home types. Home selection is often made to sample from a targeted sub-group within the population or explicitly to capture as much variability in the exposed population as possible.

The PIAMF approximates the expected F_{inf} across a set of homes based on population probabilities of window opening, expected distributions of home properties based on easily determined characteristics (such as age and foundation type), and average seasonal weather and pollutant conditions. The PIAMF is intended to produce the season average distribution across the population of homes in a given geographical area. Measured F_{inf} values are used to assess the impacts of changes in outdoor concentrations on indoor concentrations and occupant exposure. We compare the modeled F_{inf} distributions for a given region with those measured for homes from the same region to explore similarities and differences in the distributions that are estimated by the two approaches. Table 3 provides a summary of studies that have measured F_{inf} for more than 20 homes in a U.S. city. The majority of the studies measured indoor and outdoor sulfur content of $PM_{2.5}$, enabling calculation of F_{inf} .

For each city included in Table 3, we ran the PIAMF for the subset of the housing sample located in the same state and climate zone as the city with measured data that are described as “urban”. A diagram of the comparison is shown in Figure 2B. For all cities except Seattle, we compared the sulfur derived measured F_{inf} values with the week-average modeled AS F_{inf} . For Seattle, we compared the measurement derived $PM_{2.5}$ F_{inf} with the week-average modeled $PM_{2.5}$ F_{inf} . The PIAMF results are the aggregated distributions of 15 repeated runs with all parameters assigned anew for each model execution. Presentation of results include both within and between home variability. PIAMF results were calculated for the given region in the same season/weather as the measurements.

Table 3 Studies with reported infiltration factors (F_{inf}) based on a component of $PM_{2.5}$.

Study Name	Reference	Location (number of homes measurement periods ¹)
MESA Air (MA)	(Allen et al. 2012)	Baltimore, MD (39/48), Chicago, IL (28/40), Los Angeles, CA (53/80), New York, NY (26/24), Rockland County, NY (11/12), St. Paul, MN (23/56), Winston-Salem, NC (39/47)
DEARS	(Wallace and Williams 2005)	Detroit, MI (74/86)
Allen	(Allen et al. 2003)	Seattle, WA (26/29)
Habre	(Habre et al. 2014a)	New York, NY (61/53)
RIOPA	(Weisel et al. 2005)	Elizabeth, NJ(NA/NA/41),Houston, TX (NA/13/48), Los Angeles, CA (14/NA/39)

¹ For Allen et al. (2012) the number of homes listed is for warm ($>18^{\circ}C$) / cold ($\leq 18^{\circ}C$) weather sampling from Figure 1, for DEARS the number of homes listed is for summer/winter, for Allen et al. (2003) the number of homes listed is for non-heating (March-September) season and heating (October-February) season from Figure 4, for Habre et al. (2014a) data is for warm (June-October) / cold seasons (November-May) from Figure 1, for RIOPA the number of homes listed is for summer/winter/all homes

RESULTS AND DISCUSSION

Example output of the PIAMF is provided in Figure 3, which presents week-average results for urban homes in IECC climate zone 4C of Washington, predominately in Seattle, for a typical week in winter. Figure 3 shows the model-calculated distributions of indoor and outdoor mass concentration resolved by the 7 size bins and 5 species for indoor $PM_{2.5}$ originating from outdoors. Each species bin includes particles of all sizes and each size bin includes particles of all species. For this location, outdoor $PM_{2.5}$ is predominately OM with the majority of mass in the central size bins. The graph also shows the mean infiltration factor (F_{inf}) for each size bin and each species bin. F_{inf} depends on AER, penetration factor, and physical and chemical loss rates. F_{inf} values are relatively similar for all species bins except AN, which has an additional loss term due to evaporation. The smallest 3 size bins have similar F_{inf} ; but as particle size increases, F_{inf} decreases due to decreasing penetration and increasing deposition. The outdoor data shown in Figure 3 is highly skewed because there are few outdoor monitoring stations in the Seattle area. There is much larger variability in the home characteristics modeled in Seattle leading to the indoor distributions being more symmetric.

Figure 3. Distributions of week-average indoor and outdoor concentrations for each $PM_{2.5}$ size bin and species (AN=ammonium nitrate, AS=ammonium sulfate, EC=elemental carbon, OM=organic mass, O=other) for the modeled Seattle housing sample during winter. Boxes span from 25th to 75th percentiles; the line inside the box is the median and the circle is the mean. Whiskers extend to the 10th and 90th percentiles. Asterisks indicate the mean infiltration factor for each size bin and species.

Cohort Comparison Results

Air Exchange Rate (AER) Comparison

Figure 4 compares modeled and measured AERs for the DEARS (Detroit) and RIOPA cohorts. The RIOPA data is subdivided by location but not season due to the limited number of measurements for each season. Detroit results are separated by season. The percentiles displayed in Figure 4 are tabulated in Table S3 of the online supplement. Modeled distributions for the RIOPA locations are wider than those for Detroit because they include results from all seasons. Modeled and measured distributions of AERs are similar in both median and spread for the all-season composite for Elizabeth NJ and for Detroit during winter, and variations for the other cities' cohorts do not appear to show systematic biases. For Los Angeles (CA) the model-calculated, all-season composite distribution has similar 25th, slightly higher median, and substantially higher mean, 75th and 90th (i.e. higher values and more spread at the upper part of the distribution) compared to RIOPA measurements. For Detroit in summer, the measured and modeled have similar medians, but in this case the measured distribution is much broader at both ends than the modeled distribution. The largest difference was seen for the all-season distribution for Houston; the modeled distribution had an interquartile (75th/25th) that was 1.5 times greater than the measured distribution and the model-calculated median was 3.2 times greater than the measured median.

Both the model-calculated and measured AERs can differ from actual time-averaged AERs due to biases inherent in each method. Discrepancies between actual and measured time-averages AERs result from 1) an under-estimation bias that results from the non-linear relationship between PFT concentration and AER when AER varies over time during the measurement period (Sherman 1989; Sherman et al. 2014) and 2) overestimation of measured outdoor air exchange in attached homes, such as apartment buildings and row homes, since

some of the measured dilution of the PFT tracer results from air entering from adjacent dwellings. Drivers of temporal variability include diurnal variations in weather drivers of infiltration and the use of windows or doors for ventilation. The passive PFT method provides the AER that would produce the observed time-averaged concentration of an indoor source if both the AER and source emission term were constant. Discrepancies between actual and modeled time-averaged AERs can result from differences between modeled values and actual conditions related to (1) window opening magnitude and temporal patterns, (2) envelope air tightness levels (which has the largest effect when there is little or no window use), and (3) temperature and wind driving forces. Since measurements are conducted over discrete intervals that may not represent the seasonal average conditions that are the targets of the model algorithms, the window and weather factors are particularly important considerations when comparing limited measurements in homes to model output.

Figure 4. PM_{2.5} dynamic model (PDM) week-average and measured study-average air exchange rates (AER) for the RIOPA and DEARS cohorts. Modeled distributions represent 15 model runs for each cohort. Box and whisker statistics are described in Figure 3 caption. Locations are Los Angeles CA, Elizabeth NJ, Houston TX, and Detroit MI in Winter (DW) and Summer (DS). Figure 2A describes the model-measurement comparison.

It is challenging with current information to completely disentangle model and measurement biases to assess specific subcomponents of our model. Given our knowledge of existing biases we can speculate as to the cause of discrepancies across the Los Angeles, Houston and the summer Detroit housing cohorts. Weather is one potential cause of discrepancies. Table S5 in the online supplement summarizes the mean and standard deviation of wind speed and temperature for the modeled and measured homes. The Detroit summer cohort shows more variability in measured AERs potentially due to deviations in window use from the average values in the modeling since winter modeled and measured AERs were comparable and

summer measured and modeled weather are similar. DEARS reported high levels of window and door opening and fan use. Of Detroit summer homes with open windows, 46% used window fans to increase airflow. Additionally 73% of homes had doors open for an average of 1.5 days during the study period. For Los Angeles, where the vast majority of homes reported window opening, the model and measurements agree well for the bottom of the distribution, but modeled AERs are higher than measured in the upper part of the distribution. This may be due to temporal variability in AER due to time varied window openings or weather variations causing underestimations in the measured AER. Modeled wind speeds are lower than measured and modeled and measured temperatures are similar indicating that the model does not overestimate the forces that impact airflow through the windows if open. The largest difference between modeled and measured values was seen for the Houston cohort. Half of the homes in Houston were mobile homes that may not be accurately simulated by the PDM, which uses data obtained primarily for site-built, single family homes. Additionally, there could be differences between modeled and actual window opening. Modeled and measured weather differences are not large enough to have a large impact.

Infiltration Factors (F_{inf}) Comparison

Model-calculated F_{inf} values using AS and AN are compared to measured F_{inf} for sulfur and nitrate in Figure 5. The values displayed in Figure 5 are tabulated in Table S4 in the online supplement. We modeled F_{inf} using AERs estimated with the model algorithm and also with the AER reported by the measurement studies. AER has a large impact on indoor concentrations and subsequently on F_{inf} . Using the measured AER would produce F_{inf} model predictions that match measured F_{inf} values if outdoor concentrations were constant, the home were perfectly well-mixed and $PM_{2.5}$ did not have non-ventilation based loss terms. We would also expect measured and modeled F_{inf} to be similar using the measured AER if there were low variability in outdoor $PM_{2.5}$ and AER.

The model runs using AERs estimated with the model algorithm provided similar F_{inf} values as the measurement ratios for Elizabeth and Houston. For Elizabeth, these results mirror the agreement on AER. For Houston, the result raises further questions about the discrepancies between modeled and measured AERs. If actual AERs were truly as different from the modeled AERs as suggested by the measured values, the modeled and measured F_{inf} values should not match as closely as they do. One possible explanation is that measurements, which are based on the passive tracer technique, underestimate the actual time-integrated outdoor air dilution rates. If the actual AERs in Houston are higher and closer to the modeled distributions, the F_{inf} distributions are expected to be closer to the values modeled using model estimated AERs than if the reported measured AERs reflect outdoor air ventilation rates. Window opening behavior could potentially increase temporal variability in actual AERs and cause measurement bias. Another possibility is that mobile homes – which comprised half of the Houston sample – may not be well mixed when windows are open.

For Los Angeles, the modeled F_{inf} distribution is lower than the measured distributions when using the modeled AERs (which are higher than measured values) or if the measured airflow is assumed to be correct and all airflow has the unity penetration factor associated with air moving through open windows. As we hypothesized with Houston, the measured AER values may be biased low due to the high window opening rates seen in Table 2. Another possibility may be imperfect mixing in the home when windows are open, measurement error, or an indoor source in the case of indoor/outdoor ratios over 1.0. For the Los Angeles data, 7 homes had measured indoor/outdoor ratios of sulfur over 1.0 and 16 homes had ratios over 0.9.

For Detroit-Winter AS, the model runs using AERs estimated with the model algorithm predict lower F_{inf} values than measured. The measured values match well to modeled values using measured AER assuming all air is entering through the windows. AER values for Detroit-Winter matched well between model and measurements indicating that the measured Detroit houses may have higher $PM_{2.5}$ penetration or lower deposition values than those measured or that actual AERs are higher than measured or modeled estimates. The measured F_{inf} based on nitrate is lower than expected if this is the case. For Detroit-Summer, Distributions of AN and AS F_{inf} from model runs using AERs estimated with the model algorithm have smaller IQRs as would be expected from the difference in modeled and measured AERs. Modeled distributions using measured AER values assuming all airflow is through the windows most closely match measured distributions; this suggests that the measured AERs may more accurately reflect the actual AERs (compared to model estimates) that occurred during the measurement periods.

Figure 5. Modeled week-average $PM_{2.5}$ dynamic model (PDM) and measured study-average infiltration factors (F_{inf}) for the RIOPA and DEARS cohorts. F_{inf} are modeled using AERs derived from a full PIAMF run and with AERs and outdoor concentrations taken from the measured values (PIAMF run using measured AER) assuming all airflow is entering through the windows ($P=1$) or through the walls ($P<1$). Modeled distributions represent 15 repeated model runs. Box and whisker statistics as noted in Figure 3 caption. AS indicates that measured F_{inf} are derived from indoor/outdoor $PM_{2.5}$ sulfur content ratios and modeled values are the indoor/outdoor ammonium sulfate ratio. AN indicates that measured F_{inf} are derived from indoor/outdoor $PM_{2.5}$ nitrate content ratios and modeled values are the indoor/outdoor ammonium nitrate ratio. Figure 2A describes the model-measurement comparison.

Regional Comparison Results

Several measurement studies have sought to estimate regional distributions of F_{inf} based on measurements in a limited number of homes. We compare PIAMF regional F_{inf} estimates to F_{inf} regional estimates derived from measured data to explore whether the model provides any new or different information about this important process. A diagram of the comparison is shown in Figure 2B. Seasonal and annual results are shown in Figure 6. Citations and summary statistics for the measurement studies are provided in Table 3. The locations are ranked from left to right by decreasing number of heating degree-days. The intent of this

comparison was to assess whether the PIAMF and measurement studies predict substantially different F_{inf} distributions for the same geographical region. We compare distributional inter-quartile ranges (IQRs) to determine if there are substantial differences in predicted spread of the distributions. We also compare mean and median values to access relative shifts in distributions.

The top panel of Figure 6 shows comparisons for summer/warm weather. The mean IQR for all locations is similar for modeled (IQR=0.21) and measured (IQR=0.24) distributions; however there are large model and measurement differences for some locations. Of the 13 locations, 8 have larger measured IQRs than modeled, 5 have measured IQRs 1.5 times larger than modeled, and 1 has an IQR 2.5 times larger than modeled. For the 13 locations, mean and median measured F_{inf} values are, on average, 12% and 14% higher than modeled respectively. Mean and median values for measured distributions are higher than modeled for 9 and 10 locations respectively. Measured mean and median values of location specific F_{inf} distributions were within 10% of modeled for 4 and 4 locations and within 25% for 10 and 9 locations. The results indicate that summer F_{inf} values reported by measurement studies are higher and more variable than those estimated by the PIAMF for most cities / regions. One possible cause for this systematic difference is more window opening occurring during measurement events than the model assumes to occur as a seasonal average.

The middle panel of Figure 6 shows comparisons for winter/cold weather. As with summer, the mean IQR for all locations is similar for both modeled (IQR= 0.19) and measured distributions (IQR=0.19). The number of cities with large differences in model and measurement derived IQRs is smaller for winter than for summer. Among the 13 locations, 8 have measured IQRs that are larger than modeled though none were more than 40% greater than the modeled IQR. For the 5 locations with larger IQRs for modeled distributions, 3 have IQRs more than 20% larger than measured. For the 13 locations, mean and median measured F_{inf} values are, on average, 16% and 18% higher than modeled. Measured mean and median values of location specific F_{inf} distributions are within 10% of modeled for 6 and 6 locations and within 25% for 10 and 9 locations. Similar to the summer comparison, measurement studies report higher regional F_{inf} values with more within-region variability than the model estimates. Differences in window opening are unlikely to drive model/measurement differences in winter. The differences may result from higher levels of infiltration occurring during measurements as compared to the model-estimated infiltration rates. Differences in actual and modeled weather may also drive differences.

The bottom panel of Figure 6 compares annual F_{inf} distributions. Modeled distributions have equal contributions from all four seasons. Measured distributions are not equally dispersed over the year. The mean IQR for all locations are similar for both modeled (IQR= 0.21) and measured distributions (IQR=0.24) and are similar to those for summer/warm weather. Ten locations have measured IQRs that are larger than modeled, 6 are more than 25% larger and 2 are more than 50% larger. For the 13 locations, mean and median measured F_{inf} values are, on average, 24% and 19% higher than modeled respectively. Measured mean and median values of location specific F_{inf} distributions are within 10% of modeled for 5 and 4 locations and within 25% for 6 and 8 locations. Again measured distributions have larger spreads and higher mean/median values than modeled.

There are several potential causes of differences between the measured and modeled distributions. We are modeling the entire stock in the area using seasonal average conditions while measurement studies can only measure a set number of homes for a limited number of

days. Homes that volunteer for monitoring may not represent the populations in the area, either in terms of average conditions or of the variability. Half of the homes in the RIOPA dataset reported being low income which can be an indicator of a set of homes with more leakage than a typical home (Chan et al. 2013) and less access to air conditioning than the general population (US EIA 2009). The MESA air study intentionally selected homes to increase variability in their sample; that may play a factor in those homes having more variability than the representative housing sample. Additionally, the variability in weather during discrete measurements will induce more variability in measured F_{inf} distributions than modeled distributions across homes being simulated using seasonal average conditions. The modeling assumptions made about window opening and thermostat settings, described in the methods and online supplement, also may not reflect the behaviour of occupants in the measured homes.

Figure 6. Comparison of measured study-average infiltration factor (ratio of indoor/outdoor sulfur) to modeled week-average ratios of indoor/outdoor AS. PIAMF modeling results are for all homes in the same state and climate zone as the measurement locations. N values represents the number of homes with measurements; results only shown for N>10. Refer to Figure 3 for descriptions of box and whiskers. Annual average PIAMF results are the

aggregate of runs for each of the four seasons (summer, winter, fall, and spring). Study details are listed in Table 3. Figure 2B describes the model-measurement comparison.

CONCLUSIONS

We expanded the Population Impact Assessment Modeling Framework (PIAMF) to model PM_{2.5} concentrations in the US housing stock. Limited data exist on concentrations and origins of indoor PM_{2.5} across the housing stock especially at short time scales required for assessing episodic exposures. By modifying the PIAMF to include PM_{2.5} we have developed a powerful tool to assess concentrations, exposures and cost effective exposure controls.

One goal of this paper was to assess the model's ability to estimate indoor concentrations of PM_{2.5} originating outdoors. Modeled AER and F_{inf} values for the RIOPA and DEARS housing cohorts agreed reasonably well with measured values by group. The model/measurement AER comparison does not seem to show any systematic biases. Due to limitations in both measurement and model based methods for estimating whole house air exchange rate (AER), we could not fully disaggregate model errors from measurement errors. Accurate measurements of time averaged AER in homes and not just equivalent AER would significantly aid in model assessment and improvement. Model/measurement comparisons of infiltration factors appear to agree reasonably well. Additional data on particle penetration, particle deposition, regional window opening behavior, and the potential for ventilation to "short-circuit" and not result in whole house dilution of pollutants would aid in further model assessment.

A separate goal of this analysis was to compare PIAMF-derived and measurement-derived estimates of regional infiltration factors. We compared modeled infiltration factors to the results of measurement studies conducted in 11 US locations. Across locations, modeled and measured inter-quartile ranges for infiltration factors were within 0.03 indicating similar estimates of distribution spread on average with larger variations at specific locations. Measured mean and median F_{inf} values are, on average, higher than modeled values. Better characterization of the measured housing cohorts would allow for better model/measurement comparison.

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