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Predictions and determinants of size-resolved particle infiltration factors in single-family homes in the U.S.

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A B S T R A C T

Because people spend the majority of their time indoors and particles of outdoor origin infiltrate into buildings with varying efficiencies, human exposure to outdoor particles often occurs indoors. Relying on ambient measurements of particle concentrations alone can result in significant exposure misclassification in epidemiological studies; however, there remains a need to improve fundamental knowledge of the variation of particle infiltration across the building stock, particularly in residences. Therefore, this work develops a Monte Carlo simulation tool to predict the statistical distribution of time-averaged size-resolved indoor proportions of outdoor particles, or 'infiltration factors', for 0.001–10 μm particles across the U.S. single-family residential building stock. The model is then used to estimate the likely bounds of size-resolved infiltration factors and to identify the most important influencing factors using best available data for nationwide distributions of several model inputs, including air exchange rates, envelope penetration factors, deposition rates, and others. Results suggest that size-resolved infiltration factors vary highly across U.S. residences, which is consistent with existing experimental data. Size-resolved infiltration factors were strongly dependent on home characteristics and were predicted to vary by a factor of ~20 to more than 100 from the least protective of homes (99th percentile) compared to the most protective (1st percentile), depending on particle size. These results suggest that a wide variability in size-resolved infiltration factors among U.S. residences should be accounted for in future epidemiology studies. This work also identifies several existing data gaps that should be addressed to improve knowledge of size-resolved infiltration factors in homes.

1. Introduction

Elevated ambient concentrations of particulate matter, including $PM_{2.5}$, PM_{10}, and ultrafine particles (UFP, <0.1 μm), are consistently linked with adverse health effects [1–9]. These studies typically use ambient concentration measurements from central-site monitors. However, because Americans spend the majority of their time indoors (and most of that time at home) [10], and particles of outdoor origin can infiltrate and persist in buildings with varying efficiencies [11–17], relying on ambient measurements alone can result in significant exposure misclassification for a large portion of the population [18–21].

Several recent studies have attempted to address this exposure misclassification and elucidate the important determinants of the infiltration and persistence of outdoor particulate matter into residential indoor environments. One approach involves field measurements of indoor and outdoor particulate matter concentrations in a large number of residences, gathering information on home characteristics and occupant behaviors by questionnaires and building assessments, and using regression analyses and mass balance principles to identify predictors of indoor–outdoor ratios in the absence of indoor sources [22–27]. Another approach involves estimating indoor exposures to ambient particulate matter using mass balance models that incorporate more fundamental particle transport and control mechanisms, such as particle penetration factors through building envelopes, air exchange rates, deposition rates, removal by air-conditioning systems, and human activity patterns and behaviors [28–34].

Both approaches have shown that large variations in indoor exposures to ambient particulate matter can result from differences in both building characteristics such as envelope airtightness and

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human activities such as window opening. Accounting for these variations is an important step to improve exposure estimates for epidemiology studies. However, these same approaches are often limited in their representative sample sizes, their assumptions for important building input parameters, or in their focus on particular particle classes, sizes, or chemical constituents. Therefore, this work attempts to improve upon existing modeling approaches by developing a Monte Carlo simulation tool for predicting the statistical distribution of time-averaged size-resolved indoor concentrations of outdoor particulate matter across the U.S. single-family residential building stock. The tool utilizes a time-averaged size-resolved particle number balance on 0.001–10 μm particles in a well-mixed indoor environment and is integrated with best available data on influential building-related input parameters to predict time-averaged indoor proportions of outdoor particles in U.S. residences.

Results are intended to demonstrate the likely statistical bounds and distributions of heterogeneity in size-resolved indoor–outdoor particle relationships (in the absence of indoor sources) across the building stock and to provide a model framework for others to use in future exposure and epidemiology studies as new input data are acquired. Results from these simulations are also used to explore the ability of the model to use outdoor particle size distributions to predict the likely distributions of time-averaged indoor concentrations of particular classes of particulate matter encountered across the building stock, including ultrafine particle number concentrations and $PM_{2.5}$ mass concentrations. Finally, this work also highlights the importance of particular building characteristics as determinants of particle infiltration factors, which serves to identify data gaps in the existing literature and inform future field studies on ongoing measurement needs.

2. Methods

Our simulations utilize a time-averaged, well-mixed number balance to predict the proportion of outdoor particles 0.001–10 μm in diameter found inside residences due to a combination of infiltration and window opening (i.e., natural ventilation) for outdoor air exchange. Similar number or mass balance approaches have been used in other studies [35–40], but this approach differs by incorporating best available data for important building factors and likely statistical distributions of window opening behaviors, central forced-air HVAC system ownership, and HVAC filter ownership into a large Monte Carlo simulation. The model framework and relevant input parameters are described in the next sections.

2.1. Model framework

The long-term, time-averaged number balance on indoor particles of diameter *i* of outdoor origin in a well-mixed space used for each modeled home is shown in Equation (1).

$$F_{i,\text{inf}} = \frac{C_{i,\text{in}}}{C_{i,\text{out}}} = \frac{P_i\lambda}{\lambda + k_{i,\text{dep}} + \lambda_{\text{HVAC}} f_{\text{HVAC}} \eta_{i,\text{HVAC}}} \tag{1}$$

where $F_{i,\text{inf}}$ = time-averaged size-resolved infiltration factor (–); $C_{i,\text{in}}$ = time-averaged size-resolved indoor concentration of particles of diameter i (#/cm^3); $C_{i,\text{out}}$ = time-averaged size-resolved outdoor concentration of particles of diameter i (#/cm^3); P_i = time-averaged size-resolved envelope penetration factor (–); λ = time-averaged air exchange rate (AER, 1/h); $k_{i,\text{dep}}$ = time-averaged size-resolved particle deposition rate (1/h); λ_{HVAC} = recirculation rate through a central forced-air HVAC system, if applicable (1/h); f_{HVAC} = time-averaged fractional operation time of the HVAC system, if applicable (–); and $\eta_{i,\text{HVAC}}$ = size-resolved particle removal efficiency of a filter installed in the HVAC system, if applicable (–).

Terms in the numerator account for outdoor sources alone and terms in the denominator account for a number of removal mechanisms, including air exchange, surface deposition, and HVAC filtration. Input parameters that are defined on a time-averaged basis take into account both fundamental building characteristics applicable for periods when doors and windows are closed (referred to as 'closed-window' values), as well as adjusted values of those same characteristics during periods when the building is influenced by human interaction (primarily by altering values during periods of open windows, which will increase air exchange rates, penetration factors, and deposition rates).

Each modeled home is uniquely described first by estimating its time-averaged air exchange rate (λ) using Equation (2), which accounts for estimates of both closed-window and open-window air exchange rates.

$$\lambda = \lambda_{\text{closed windows}}\left(1 - f_{\text{open windows}}\right) + \lambda_{\text{open windows}} f_{\text{open windows}} \tag{2}$$

where $\lambda_{\text{closedwindows}}$ = the air exchange rate in a home with doors and windows closed (1/h); $\lambda_{\text{openwindows}}$ = the average air exchange rate during periods of open windows (1/h); and $f_{\text{openwindows}}$ = the fraction of time windows are open (–). The fractional time of open windows ($f_{\text{openwindows}}$) was adjusted to account for window opening only during times of mild weather, as shown in Equation (3). This same approach has been used in other recent work [31].

$$f_{\text{openwindows}} = f_{\text{mild}} f_{\text{openwindows,mild}} \tag{3}$$

where f_{mild} = the fraction of time mild weather is experienced and $f_{\text{openwindows, mild}}$ = the fraction of time windows are open during mild weather. $\lambda_{\text{openwindows}}$ is based on $\lambda_{\text{closedwindows}}$ for each home but is adjusted for the probability that windows are open either a low or high amount ($\phi_{\text{openwindows,low}}$ or $\phi_{\text{openwindows,high}}$) using a constant air exchange rate multiplier for each opening condition ($m_{\text{openwindows,low}}$ or $m_{\text{openwindows,high}}$) as shown in Equation (4). The selection of AER multipliers is described in a later section.

$$\lambda_{\text{openwindows}} = \lambda_{\text{closedwindows}}\left(\phi_{\text{openwindows,low}} m_{\text{openwindows,low}} + \phi_{\text{openwindows,high}} m_{\text{openwindows,high}}\right) \tag{4}$$

Similar to the process for estimating time-averaged air exchange rates, time-averaged size-resolved envelope penetration factors are then estimated based on size-resolved penetration factors during closed-window periods combined with the fraction of time windows are open and penetration factors are higher, as shown in Equation (5).

$$P_i = P_{i,\text{closedwindows}}\left(1 - f_{\text{openwindows}}\right) + P_{i,\text{openwindows}} f_{\text{openwindows}} \tag{5}$$

where $P_{i,\text{closedwindows}}$ = the closed-window size-resolved envelope penetration factor in a home (–) and $P_{i,\text{openwindows}}$ = the average size-resolved penetration factor during periods with windows open (–). Values for $P_{i,\text{openwindows}}$ are estimated by taking into account separate values for low and high window opening conditions as well as the probability of each opening condition, as shown in Equation (6).

$$P_{i,\text{openwindows}} = P_{i,\text{openwindows,low}}\phi_{\text{openwindows,low}} + P_{i,\text{openwindows,high}}\phi_{\text{openwindows,high}} \quad (6)$$

For high window opening conditions, $P_{i,\text{openwindows,high}}$ is assumed to be equal to 1 for all particle sizes, which is consistent with some previous studies [12]. For low window opening conditions, $P_{i,\text{openwindows,low}}$ is estimated by taking into account both closed-window penetration factors through infiltration and assuming a penetration factor of 1 for any additional air exchange provided by excess natural ventilation through open windows, as shown in Equation (7).

$$P_{i,\text{openwindows,low}} = P_{i,\text{closedwindows}}\frac{\lambda_{\text{closedwindows}}}{\lambda_{\text{openwindows,low}}} + (1)\frac{\lambda_{\text{openwindows,low}} - \lambda_{\text{closedwindows}}}{\lambda_{\text{openwindows,low}}} \quad (7)$$

Time-averaged values for $k_{i,\text{dep}}$ are also adjusted in a similar manner to account for greater particle removal during times of window opening [41], as shown in Equation (8).

$$k_{i,\text{dep}} = k_{i,\text{dep,closedwindows}}\left(1 - f_{\text{openwindows}}\right) + k_{i,\text{dep,openwindows}}f_{\text{openwindows}} \quad (8)$$

where $k_{i,\text{dep,closedwindows}}$ = the size-resolved deposition rate in a home with doors and windows closed (1/h) and $k_{i,\text{dep,openwindows}}$ = size-resolved deposition rate with windows open (1/h). Values for $k_{i,\text{dep,openwindows}}$ are adjusted in a similar manner as $P_{i,\text{openwindows}}$ by taking into account separate values for low and high window opening conditions as well as the probability of each opening condition, as shown in Equation (9).

$$k_{i,\text{dep,openwindows}} = k_{i,\text{dep,openwindows,low}}\phi_{\text{openwindows,low}} + k_{i,\text{dep,openwindows,high}}\phi_{\text{openwindows,high}} \quad (9)$$

where $k_{i,\text{dep,openwindows,low}}$ = size-resolved deposition rate with windows open a small amount (adjusted for all sizes by a constant deposition rate multiplier, α, so that $k_{i,\text{dep,openwindows,low}} = \alpha k_{i,\text{dep,closedwindows}}$) and $k_{i,\text{dep,openwindows,high}}$ = size-resolved deposition rate with windows open a large amount (adjusted for all sizes by a constant deposition rate multiplier, β, so that $k_{i,\text{dep,openwindows,high}} = \beta k_{i,\text{dep,closedwindows}}$). With the model framework outlined, the next section describes how representative input values were selected for use in the application of the model.

2.2. Values for input parameters across the U.S. single-family residential building stock

In order to perform the Monte Carlo simulations and explore the utility of the model, estimates were made of the likely statistical distributions of each of the aforementioned input parameters. These values were culled from a wide variety of sources to establish a best estimate of the statistical distribution for each input parameter in single-family homes across the U.S. building stock. We have attempted to improve upon previous infiltration modeling efforts by incorporating these input variables, most notably by incorporating likely distributions of central HVAC system and filter ownership; HVAC system runtime; size-resolved envelope penetration factors, deposition rates, and HVAC filter removal efficiencies; and increases in air exchange rates, penetration factors, and deposition rates during periods of window opening by occupants. Input data are described below, first for parameters that are independent of particle size and second for parameters that are size-resolved. We should note that some of these datasets remain quite limited and may not capture the true distribution of input values across the building stock, but the methods and results involved are still valuable for prediction and interpretation.

2.2.1. Input parameters independent of particle size

This section first describes the collection of inputs that are independent of particle size, including air exchange rates due to infiltration alone ($\lambda_{\text{closedwindows}}$), recirculation rates through HVAC systems (λ_{HVAC}), fractional operation times of HVAC systems (f_{HVAC}), window opening behavior ($f_{\text{openwindows}}$), and increases in air exchange rates during window opening ($\lambda_{\text{openwindows}}$).

2.2.1.1. Air exchange rates due to infiltration ($\lambda_{closedwindows}$). Infiltration air exchange rates (AERs) have been measured in thousands of buildings worldwide, and have been shown to vary widely both across buildings and temporally within individual buildings [42–44]. Most recently, Persily et al. (2010) modeled the statistical distribution of infiltration AERs in a sample of 209 model dwellings that represent the majority of the U.S. residential building stock [45]. Their model predictions aligned very well with existing measurements and provide the added benefit of spanning such a large fraction of the building stock. A lognormal distribution was fit to their reported percentiles by minimizing the sum of the squared errors between their reported cumulative distribution function and a model of a lognormal cumulative distribution function, resulting in a geometric mean (GM) AER of 0.44 h^{-1} (with a geometric standard deviation, GSD = 2.04). This distribution is shown in Fig. 1a.

2.2.1.2. Recirculation rates through central HVAC systems (λ_{HVAC}). For the homes that were assumed to have a central HVAC system with a filter installed, it is important to first quantify the rate of airflow through the HVAC system relative to the volume of the space that it serves (i.e., its recirculation rate with the HVAC system operating). Similar studies have typically assumed values of λ_{HVAC} [35,46]. For lack of a more robust dataset, we rely on a distribution of actual recirculation rates measured with systems operating in 17 residential and small commercial buildings (all of which utilized typical residential HVAC equipment) reported in Stephens et al. (2011) [47]. A lognormal distribution of recirculation rates was fit with a GM = 5.7 h^{-1} (GSD = 1.26); one extreme outlier was excluded because it represented a small, atypical office environment. This distribution is shown in Fig. 1b. These values are then adjusted for long-term average fractional runtime, as described below.

2.2.1.3. Fractional runtime of central HVAC systems (f_{HVAC}). Previous similar investigations have either assumed values for fractional operation times [36,46,48] or estimated them from building energy models [49]. Conversely, we compiled a database of previously measured fractional operation times in residences that were made during a variety of heating, cooling, and mild weather seasons for use in the simulations of homes assumed to have a central HVAC system. We used data from 37 homes in North Carolina [50], 17 homes in Florida [50], and 17 homes and light-commercial buildings Texas [47] to build a statistical distribution that we consider generally representative for the residential building stock. The data were lognormally distributed with a GM = 0.246, or 24.6% of the time (GSD = 1.85). This distribution is shown in Fig. 1c. Again, these data might not be entirely representative of the building stock but they are considered appropriate in the absence of more robust datasets.

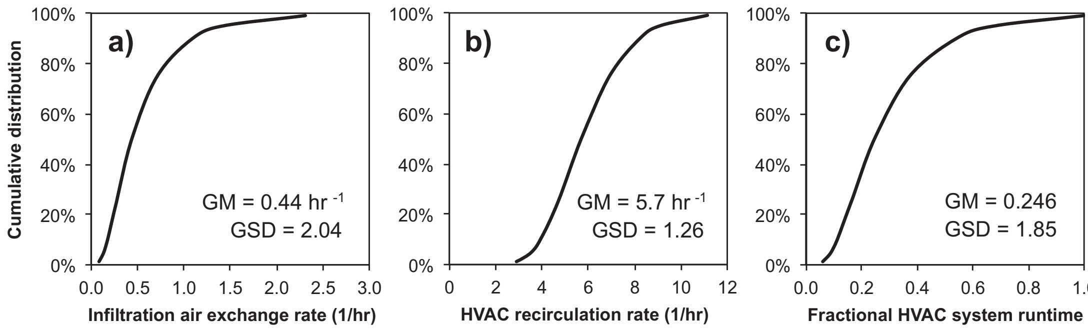

Fig. 1. Lognormal distributions of (a) infiltration air exchange rates ($\lambda_{closedwindows}$), (b) HVAC system recirculation rates (λ_{HVAC}), and (c) fractional HVAC system runtimes (f_{HVAC}) used as inputs in the simulations. GM = geometric mean and GSD = geometric standard deviation.

2.2.1.4. Fraction of window opening ($f_{openwindows}$). Window opening is an important behavior to capture accurately for exposure modeling because values of air exchange rates, penetration factors, and particle deposition rates will all increase relative to periods of infiltration only. Therefore, we culled existing literature on window opening behaviors in homes, giving priority to larger sample sizes. We also assumed that window opening occurred only during mild weather in the homes; therefore, we first fit a U.S. nationwide distribution of fractions of the year that mild weather occurs using data reported in Chen et al. (2012) [31], as shown in Fig. 2a. This assumption likely leads to a somewhat conservative estimate of periods of window openings, with the majority of homes experiencing mild weather between 20% and 60% of the time.

To assess the statistical distribution of window opening behaviors during periods of mild weather, we culled data primarily from a large study of single-family homes across the state of California [51]. We limited use of their data only to mild weather times (i.e., spring seasons, although their fall season distributions were very similar). For window opening fractions, we combined their 'low' and 'medium' opening characterizations into one 'low' window opening behavior class, which includes anywhere from only one or two windows opened slightly to as much as one or two windows open several centimeters. The 'high' window-opening scenario was used to characterize homes with at least some number of windows or doors open fully. The distribution of the fraction of time windows are open during mild weather is shown in Fig. 2b.

Because of the irregular shapes of the distributions for mild weather and window opening during mild weather, data from Fig. 2a and b were used to create a step-wise function instead of a continuous distribution. The median fraction of time with mild weather across the U.S. was ~31%. The median fraction of time with windows open during mild weather was ~40%. Therefore, the median long-term average fraction of time that windows were open was ~13%, which is in a similar range as other studies on window opening behavior [52].

2.2.1.5. Air exchange rates during window opening ($\lambda_{openwindows}$). Using data from Price and Sherman (2006) [51], we assumed that when windows are open in a home, 20% of the time they are open to a large extent (i.e., 'high' window opening) and 80% of the time they are open to a low or moderate amount (i.e., 'low' window opening). These fractions were assumed to be constant across all homes due in part to the findings in Price and Sherman (2006) [51] and in part to a lack of more detailed distribution data. We then assumed values for an air exchange rate multiplier for each window opening scenario ($m_{openwindows,low}$ and $m_{openwindows,high}$). We assumed that the AER during times of low window opening was two times higher than the home's closed-window infiltration AER and four times higher during times of high window opening; therefore $m_{openwindows,low} = 2$ and $m_{openwindows,high} = 4$.

These multipliers are assumed constant in each home and were derived from measurements reported in both Wallace et al. (2002) [42] and Marr et al. (2012) [53]. Values for AER multipliers are also similar to the mean values measured in Johnson et al. (2004) [54] with one window open and three or more windows open, respectively, as well as those utilized in Chen et al. (2012) [31]. After accounting for window opening behavior during times of mild weather, the median air exchange rate (0.44 h^{-1}) increased to a long-term average of 0.50 h^{-1} (a 14% increase). The bottom percentile of window opening increased infiltration AERs by <5% while the top increased long-term AERs by 25% or more, considered relative to the closed-window infiltration AER. Although these assumptions may introduce considerable uncertainty, we consider their use quite reasonable at this point in time.

2.2.2. Particle size-resolved input parameters

This section describes the collection of input parameters that are dependent on particle size, including envelope penetration factors (P_i), indoor deposition rates ($k_{i,dep}$), and filter removal efficiency ($\eta_{i,HVAC}$), which is also based on information on central forced-air HVAC system and filter ownership.

2.2.2.1. Penetration factors (P_i). Chen and Zhao (2011) provide an extensive review of previous measurements of size-resolved particle infiltration factors and penetration factors in residences [13]. Studies that have measured particle penetration factors in homes vary widely in their particle sizes over which the values were measured, as well as their sample sizes and estimates of uncertainty. We have not been able to identify a particular study that investigated the full range of particle sizes of interest (0.001–10 μm), so we have relied on a combination of all of the previous studies reported in Chen and Zhao [13], which summarized penetration factors of 0.01–10 μm measured in approximately 10 homes in several other studies [12,14,55–57]. We also included another

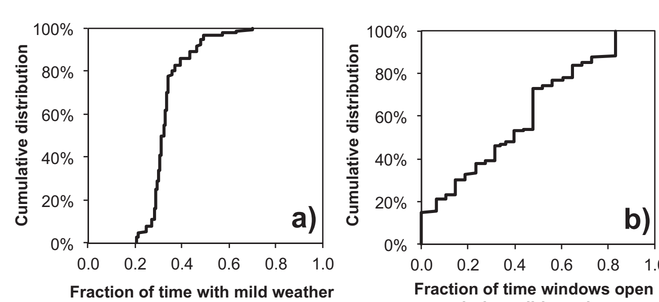

Fig. 2. Cumulative distributions of (a) the fraction of time with mild weather (f_{mild}) [31] and (b) the fraction of time windows are open during periods of mild weather ($f_{openwindows,\ mild}$) [51].

recent study in our summary [11], which also measured penetration factors of 5–100 nm particles in a test house.

There is considerable variability in these measured values of penetration factors, depending on both individual homes and particle sizes of interest. However, because sample sizes are small and we lack more robust size-resolved data, we rely on an estimate of the midpoint of the size-resolved penetration factors across any and all applicable homes included in the review in Chen and Zhao (2011) [13] with the addition of Rim et al. (2010) [11] to estimate mean values of $P_{i,\mathrm{closedwindows}}$ for each particle size. We have also extrapolated results from 1 to 10 nm, assuming a log-linear decrease toward zero for 1 nm particles.

Additionally, we have included a measure of likely variability in size-resolved values for $P_{i,\mathrm{closedwindows}}$ using relative standard deviations (RSD) from the two largest previous studies of particle penetration factors of which we are aware. Williams et al. (2003) reported mean (±s.d.) values for penetration factors of $PM_{2.5}$ of 0.72 ± 0.21 in 37 homes in North Carolina (RSD = 29%) [58]. Similarly, Stephens and Siegel (2012) reported normally distributed values of penetration factors for submicron particles (0.02–1 μm) with a mean (±s.d.) of 0.47 ± 0.15 in 19 homes in Texas (RSD = 32%) [15]. We have therefore assumed a normal distribution with a relative standard deviation of 30% for all of the size-resolved penetration factors utilized in this study, which provides a reasonable estimate of the statistical bounds on $P_{i,\mathrm{closedwindows}}$ in the absence of better information. We also assume that values for every particle size increase or decrease together in the same direction and the same relative magnitude. The mean (±one standard deviation) size-resolved penetration factors used in the simulations are shown in Fig. 3a.

Penetration factors during periods of window opening are estimated according to Equations (5)–(7). In this procedure, we assume that when windows are open a small amount (i.e., 'low' opening), some fraction of outdoor air still enters through the envelope ($\lambda_{\mathrm{closedwindows}}/\lambda_{\mathrm{openwindows,low}}$) with the closed-window penetration factor ($P_{i,\mathrm{closedwindows}}$). Any additional amount of outdoor air ($1 - \lambda_{\mathrm{closedwindows}}/\lambda_{\mathrm{openwindows,low}}$) is assumed to enter through open windows with a penetration factor of 1. Therefore the time-averaged envelope penetration factor will always be greater than or equal to the closed-window envelope penetration factor. When windows are open a large amount, we assume that the penetration factor for every particle size is equal to unity.

2.2.2.2. Indoor deposition rates ($k_{i,dep}$). Another important size-resolved loss mechanism in indoor environments is particle deposition to indoor surfaces ($k_{i,\mathrm{dep}}$). A previous size-resolved particle infiltration modeling study estimated deposition rates using physical models [35], but we rely on a range of size-resolved deposition rates measured in real residential environments. In one of the largest investigations of size-resolved particle deposition rates in residences of which we are aware, He et al. (2005) reported size-resolved measurements of $k_{i,\mathrm{dep}}$ in 14 homes in Australia under two different ventilation conditions: doors and windows closed (infiltration AER) and with some doors and windows open (natural ventilation) [41]. The same study also reported size-resolved deposition rates measured in several other residential studies (mostly from U.S. homes), and noted large differences between their measured values and others, due perhaps to differences in estimation methods and/or the type of aerosol source utilized (deposition rates vary according to particle density and shape). Given these issues, we used a polynomial curve to fit the shape of size-resolved deposition rates from He et al. (2005) [41], but adjusted the mean values downward to better reflect the midpoint of the size-resolved results from other studies in U.S. homes. The resulting polynomial curve yields $k_{i,\mathrm{dep,closedwindows}} = 1.06 + 1.83 \times (\log D_p) + 1.65 \times (\log D_p)^2$, where D_p is in μm. We also used the relative standard deviations (mean RSD of ~68% across all particle sizes) reported in He et al. (2005) [41] to establish bounds on the likely statistical distribution of deposition rates for all particle sizes in homes across the building stock. These values are shown in Fig. 3b.

Finally, increased AERs with windows open will increase indoor air speeds, which will in turn increase particle deposition rates [59]. Therefore, we estimated size-resolved deposition rate multipliers with windows open (α and β) using the same data from He et al. (2005). We used their polynomial fits for mean size-resolved deposition rates from Figs. 3 and 4 in their manuscript for periods of windows closed and windows open, respectively. We then calculated the ratio between $k_{i,\mathrm{dep,openwindows}}$ and $k_{i,\mathrm{dep,closedwindows}}$ and averaged the ratio across all particle size bins. The resulting value was approximately 1.7; that is, with windows open, the mean deposition rate across all particle sizes increased approximately 70% over that measured during periods with windows closed. Thus we assume that $\beta = 1.7$ with windows open a large amount. Additionally, we estimated that $\alpha = 1.23$ for periods with windows open a small amount, based on an assumed linear relationship between deposition rates and air exchange rates (AERs were estimated as two times higher with windows open a low amount and four times higher with windows open a large amount; thus $\alpha = (2 - 1)/(4 - 1) \times \beta = 1.23$). We should note that this method might not accurately capture the true variability of open window deposition rates across the building stock, but these assumptions are still appropriate for the purposes of this work in the absence of more robust data.

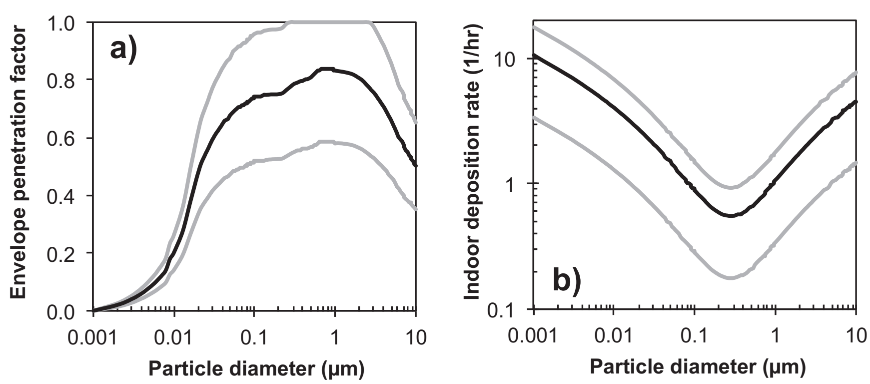

Fig. 3. Size-resolved (a) particle penetration factors ($P_{i,\mathrm{closedwindows}}$) and (b) deposition rates during periods of closed-window infiltration ($k_{i,\mathrm{dep,closedwindows}}$). Black lines represent mean values and gray lines represent ± one standard deviation. Mean deposition rates are estimated as follows: $k_{i,\mathrm{dep,closedwindows}} = 1.06 + 1.83 \times (\log D_p) + 1.65 \times (\log D_p)^2$.

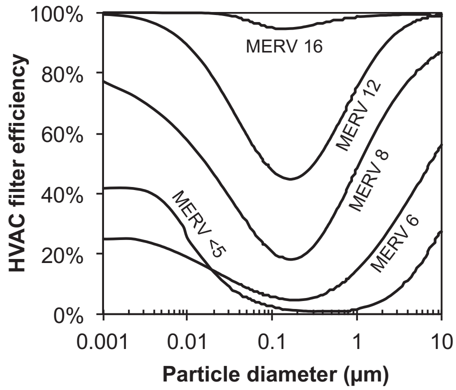

Fig. 4. Size-resolved particle removal efficiency ($\eta_{i,\mathrm{HVAC}}$) for the five classifications of filters used in this study: MERV <5, MERV 6, MERV 8, MERV 12, and MERV 16.

2.2.2.3. Filter removal efficiency (η_i). The presence and use of air-conditioning and forced-air heating has been shown to be a significant predictor for particulate matter infiltration factors in field studies [23,25,60,61]. This decrease is likely attributed in part to particle filters installed in HVAC systems; even if a very low efficiency filter is used, HVAC filters can increase indoor particle loss rates due to typically large recirculation rates through HVAC systems [49,62]. Higher efficiency filters intuitively have a greater effect [63–65]. A wide range of particle filters exist in the residential market, so it is necessary to understand both (i) the removal efficiency of a range of commonly available HVAC filters and (ii) HVAC filter ownership across the building stock in order to estimate the impacts that HVAC filtration likely has on size-resolved particle infiltration factors in U.S. residences. We ignore deposition to HVAC ductwork surfaces for lack of more robust data from measurements in real homes [66,67]. We also ignore the use of any portable air cleaners for this effort.

HVAC filters are typically tested for particle removal efficiency only in laboratory settings. ASHRAE Standard 52.2 is the most commonly used test standard in the U.S [68]. The standard assigns filters a Minimum Efficiency Reporting Value (or MERV) according to the ability of the filter to remove 0.3–10 μm particles. However, to extend the particle size range below 0.3 μm, we utilize polynomial fits for recent measurements of size-resolved particle removal efficiency reported for a range of commercially available HVAC filters in Hecker and Hofacre (2008) [69], which reported removal efficiencies for particles as small as 0.03 μm. Additionally, particle removal efficiency values for the lowest efficiency filters (MERV <5) were taken from Waring and Siegel [46]. Size-resolved HVAC filter removal efficiencies for five broadly representative classes of filters are shown in Fig. 4.

2.2.2.4. HVAC system and filter ownership. Surprisingly little information exists on the distribution of types of filter ownership across the residential building stock. In a survey of 17 homes in Austin, TX with central HVAC systems, Stephens and Siegel (2012) observed the following distribution of installed HVAC filter types: five homes utilized MERV <5; nine homes utilized MERV 6–8; two homes utilized MERV 11–12; and one home utilized MERV 16 [15]. In a survey of three pilot test homes, Offermann (2009) reported that two utilized MERV 6 filters and one utilized a MERV 8 filter [44]. A conversation with an anonymous contact in the residential filtration industry confirmed that ~75% of their filter sales were MERV 7 or lower. Therefore, we assumed a distribution of HVAC filter ownership in U.S. single-family residences, as shown in Table 1. This assumed distribution should be interpreted with some caution, but we are not aware of more reliable information at this time. Differences in removal efficiencies between adjacent MERV categories are often small, so only five representative filter types were assumed.

Table 1
Estimate of HVAC filter ownership across the residential building stock (for homes with HVAC systems).

Filter type	% Ownership
MERV < 5	25%
MERV 6	30%
MERV 8	30%
MERV 12	10%
MERV 16	5%

2.3. Monte Carlo simulations

A Monte Carlo approach was used to predict the likely distribution of size-resolved infiltration factors in single-family residences across the U.S. building stock and to demonstrate the utility of the model framework using the aforementioned statistical distributions of each input parameter. Similar approaches have been used in other recent indoor air quality investigations [70–72]. A total of 100,000 simulations were performed for individual geometric mean (GM) particle diameters for 102 bins between 0.001 and 10 μm. Because approximately 65% of residences in the U.S. have central HVAC systems [73], 65,000 simulation cases were assigned an HVAC system; the other 35,000 were assumed to have no central HVAC system. The number of simulations was chosen such that the smallest group of simulated homes (those with MERV 16 HVAC filters) was still large enough to capture a wide range in predicted values and achieve repeatable results ($n = 3250$ for MERV 16). Simulations were performed in MathWorks MATLAB R2012a.

Each simulation began by sampling size-independent parameters randomly from the distributions in Fig. 1. Closed-window values for size-resolved deposition rates and penetration factors were also randomly sampled from the individual distributions in Fig. 3 (and scaled in the same direction and relative magnitude for each particle size for each percentile). Values for penetration factors, filter removal efficiencies, and HVAC system runtimes were bound between 0 and 1. Deposition rates were bound to values greater than zero. At this point, each modeled home was uniquely identified in the simulations with these closed-window building characteristics. Subsequently, the time-averaged fractions of mild weather, fraction of window opening, and type of filter used (if the home had an HVAC system) were sampled at random according to the distributions in Fig. 2 and the likelihood of HVAC filter ownership in Table 1.

Each parameter was assumed to be independent of all other parameters, which may not be an entirely realistic assumption. For example, closed-window envelope penetration factors were recently shown to be correlated with AER [15], which, if accounted for, would likely extend both the upper and lower bounds of our model results. However, the relationships between many of these parameters are not yet well known, particularly on a size-resolved basis. Additionally, there is some evidence that occupants may be more likely to open windows in homes without central HVAC systems during a wider range of seasons [52], but unfortunately we cannot account for this because we are not aware of robust data on these relationships.

Subsequently, time-averaged AERs, penetration factors, and deposition rates were estimated according to Equations (3)–(9). Finally, each sampled time-averaged input parameter was used to estimate the time-averaged indoor proportion of outdoor particles of diameter i in each simulated home according to Equation (1).

Results were then explored in order to predict the likely distribution of size-resolved infiltration factors across the U.S. single-family residential building stock using these best available data. Results were also used to predict the likely distribution of absolute number concentrations of indoor particles of outdoor origin across the building stock, as well as indoor UFPs and $PM_{2.5}$ of outdoor origin, based on assumptions for time-averaged outdoor particle size distributions, particle shape, and particle density. Finally, a sensitivity analysis was performed by using a multiple linear regression with the input and output data for each particle size in order to demonstrate the most influential parameters governing size-resolved infiltration factors.

3. Results and discussion

3.1. Distributions of predicted size-resolved infiltration factors

Estimates of the likely distribution of time-averaged size-resolved infiltration factors ($F_{i,\mathrm{inf}}$) across the U.S. single-family residential building stock made using the model framework are shown in Fig. 5. Seven percentiles are shown based on the results from the 100,000 simulations, spanning a range from the 1st percentile to the 99th percentile. Minimum and maximum values are excluded for clarity.

For some particle sizes in Fig. 5, $F_{i,\mathrm{inf}}$ are estimated to vary by a factor of ~20 to more than 100 from the 99th percentile to the 1st percentile, with an average of ~60 across all particle sizes between these two percentiles. Differences within the interquartile range are not as stark but are still meaningful and likely important to capture: the 75th percentile $F_{i,\mathrm{inf}}$ is typically between a factor of 2–4 greater than the 25th percentile (with a mean of ~3.1 across all particle sizes). Overall, these results suggest that indoor concentrations of outdoor particles can vary highly among residences across the U.S. building stock, particularly between the most protective homes and the least protective homes and depending in large part on particle size.

To aid in the interpretation of the size-resolved results and aid in future binned analyses, these same data are also shown averaged over seven particle size bins. Box plots of their distributions are displayed in Fig. 6. The size bins included: <0.01 μm, 0.01–0.05 μm, 0.05–0.10 μm, 0.1–0.5 μm, 0.5–1 μm, 1–5 μm, and 5–10 μm.

According to Fig. 6, we estimate that 0.1–0.5 μm particles of outdoor origin are most likely to exist indoors in the greatest numbers ($F_{0.1-0.5,\mathrm{inf}}$: GM = 0.29; GSD = 1.94), followed by 0.5–1 μm particles ($F_{0.5-1,\mathrm{inf}}$: GM = 0.25 and GSD = 2.05). This is intuitive because most of the fundamental forces that govern particle removal are typically weakest for 0.1–0.5 μm particles [74,75]. Larger particles (i.e., 1–5 μm and 5–10 μm) are estimated to have lower time-averaged values of $F_{i,\mathrm{inf}}$ ($F_{1-5,\mathrm{inf}}$: GM = 0.13 and GSD = 2.38; $F_{5-10,\mathrm{inf}}$: GM = 0.07 and GSD = 2.63). Finally, values of $F_{i,\mathrm{inf}}$ for ultrafine particles are also estimated to be lower than 0.1–1 μm particles ($F_{0.05-0.1,\mathrm{inf}}$: GM = 0.20 and GSD = 2.12; $F_{0.01-0.05,\mathrm{inf}}$: GM = 0.10 and GSD = 2.37; and $F_{0.001-0.01,\mathrm{inf}}$: GM = 0.01 and GSD = 2.92). Estimates of $F_{i,\mathrm{inf}}$ in both Figs. 5 and 6 also show that in some homes indoor proportions of outdoor particles are very small or even negligible, particularly for the bottom percentiles. Conversely, values of $F_{i,\mathrm{inf}}$ for some particle sizes may approach unity for some homes in the 99th percentile or above.

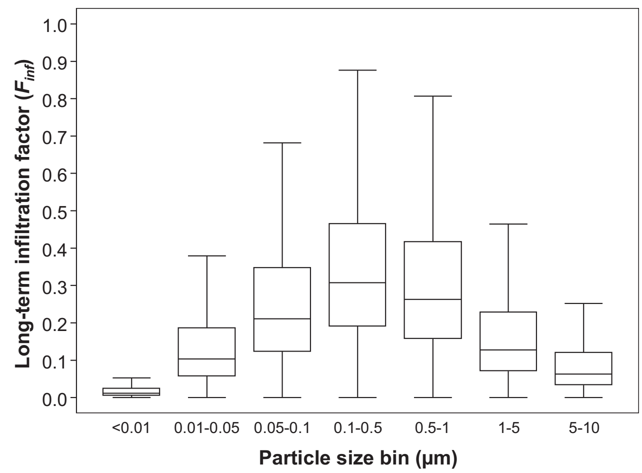

Fig. 6. Box plots of predicted time-averaged infiltration factors (F_{inf}) across the U.S. single-family residential building stock, averaged over seven particle size bins. Boxes represent the interquartile range (IQR) and whiskers represent adjacent values (i.e., those within 1.5 times the IQR). Outliers are excluded for clarity.

To provide some comparison to existing measurements, other studies have measured similar distributions of $F_{i,\mathrm{inf}}$ for particle number concentrations in homes, although large samples seldom include size-resolved measurements. For example, Kearney et al. (2011) measured values of F_{inf} for submicron (non-size-resolved) particles in over 40 homes in Windsor, Ontario ranging from ~0.03 to ~0.9 with a median of ~0.19–0.27 depending on season and estimation method [16]; our model results for submicron particles are generally in line with these measurements (Fig. 6), although exact comparisons cannot be made because particle size distributions were not measured in their work. Similarly, Bhangar et al. (2011) estimated values of F_{inf} for submicron particles from ~0.1 to ~0.5 in seven homes in California; again, our results align generally in this range but an exact comparison cannot be made in the absence of knowledge on their size distributions [76].

Comparing our results to a very limited number of size-resolved field measurements, our modeled 25th to 50th percentile size-resolved UFP estimates follow a similar pattern to those measured in Rim et al. (2010) inside a test house with closed windows, with an average $F_{i,\mathrm{inf}}$ for 0.1 μm particles near ~0.2 and declining towards less than 0.05 for 0.005 μm particles [11]. Similarly, the 75th to 90th percentiles in this work follow a similar profile to those in Rim et al. (2010) measured with windows opened, with an average $F_{i,\mathrm{inf}}$ for 0.1 μm particles near ~0.4 and declining towards less than 0.2 for 0.01 μm particles [11]. These results provide some validity to our approach as the test home in Ref. [11] was of moderate airtightness [77], estimated to be

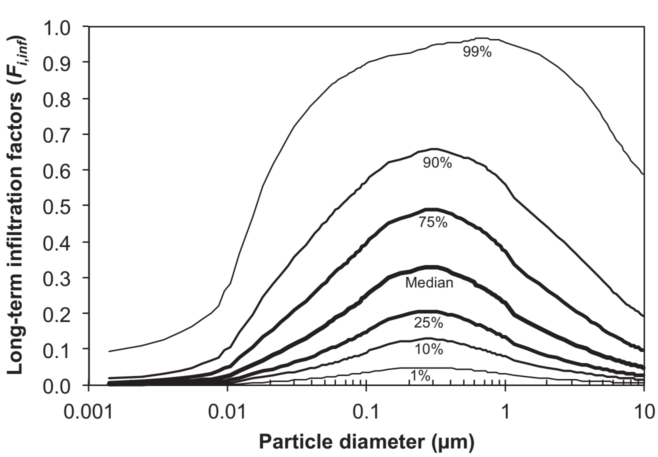

Fig. 5. Estimate of the distribution of time-averaged size-resolved infiltration factors ($F_{i,\mathrm{inf}}$) across the U.S. single-family residential building stock resulting from the 100,000 simulations.

approximately within the 50th to 75th percentile of homes across the U.S. according to blower door results [78]. Our modeled results for the 75th to 90th percentiles values of $F_{i,\mathrm{inf}}$ for 0.01–0.2 μm particles also follow a similar trend to those measured in several apartment units in Zhu et al. (2005), particularly for one home with an HVAC system operating [12].

3.2. Mapping to outdoor particle size distributions

We here show an example of how these size-resolved estimates of time-averaged infiltration factors can also be used to estimate the indoor size-resolved indoor number concentrations based on particle size distributions for any outdoor environment. If particle densities are also known, estimates of absolute indoor proportions of outdoor particulate matter mass (e.g., $PM_{2.5}$ or PM_{10}) can also be made, as we will demonstrate. Data for long-term time-averaged size-resolved outdoor size distributions and particle densities are limited in the U.S.; therefore, we rely on previous measurements of outdoor particle size distributions in a variety of outdoor environments from one of the longer term studies of which we are aware in order to illustrate the likely bounds on distributions of indoor particulate matter of outdoor origin (specifically $PM_{2.5}$ and total UFPs).

The used dataset includes long-term outdoor data from three sites in and around Leipzig, Germany [79], including: (1) a rural background site approximately 50 km from Leipzig; (2) an urban background site on the roof of a university building within the city approximately 100 m from highly-trafficked roads; and (3) an area near a moderately-trafficked roadway near the city center (carrying approximately 12,000 vehicles per workday). These locations each have unique particle size distributions, which we herein call (1) rural, (2) urban background, and (3) urban traffic. We are not aware of similar long-term measurements in locations in the U.S., other than shorter term measurements in Los Angeles, CA and Pittsburgh, PA that were made during sampling campaigns at two EPA Supersite locations [80], although others may exist.

Mean and standard deviation particle size distributions reported in Costabile et al. (2009) were fit using a lognormal distribution with three modes [79]. Distribution statistics are shown in Table 2 and the long-term average outdoor particle size distributions are also shown graphically in Fig. 7. Only the arithmetic mean distributions are utilized herein for the long-term average. The urban and rural distributions used herein [79] were quite similar in both magnitude and shape as long-term measurements in the previously mentioned Pittsburgh field study [81].

Estimates of $PM_{2.5}$ mass concentrations for each outdoor location are also given in Table 2; these were determined by assuming spherical shape particles and a particle density of 1.0 g/cm^3 [35,46]. Estimates for long-term average outdoor $PM_{2.5}$ concentrations were as follows: $PM_{2.5,\mathrm{rural}} = 13.2$ μg/m^3; $PM_{2.5,\mathrm{urban}} = 15.0$ μg/m^3; $PM_{2.5,\mathrm{traffic}} = 17.5$ μg/m^3. Time-averaged outdoor concentrations of UFPs and total particles were estimated as ~4200 #/cm^3 and ~5600 #/cm^3 in the rural environment, ~9340 #/cm^3 and ~11500 #/cm^3 in the urban background environment, and ~19780 #/cm^3 and ~22900 #/cm^3 in the urban traffic environment.

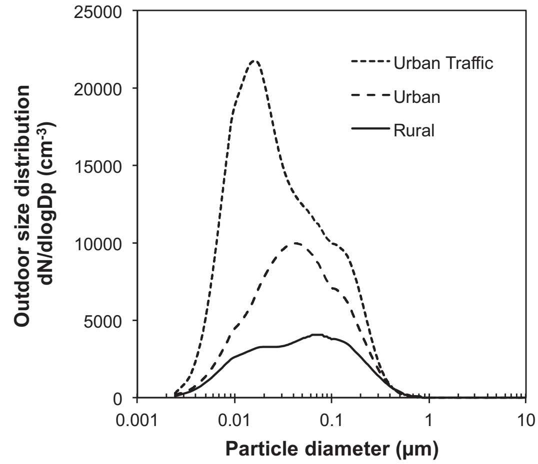

Fig. 7. Mean outdoor particle size distributions from three different environments in and around Leipzig, Germany reported in Costabile et al. (2009) [79].

The outdoor particle size distributions from each of the three locations are then used alongside the $F_{i,\mathrm{inf}}$ distributions in Fig. 5 to predict the distribution of time-averaged indoor concentrations of outdoor size-resolved particles, assuming each home is subject to the same outdoor size distribution. The results, shown in Fig. 8, are instructive for exploring how much indoor concentrations of outdoor particles can vary according to differences in outdoor particle size distributions. We did not attempt to assign rural, urban, and urban traffic environments to particular subsets of the predicted distributions based on geography, largely because we do not have enough data on input parameters to divide the modeled homes regionally.

In addition to size-resolved estimates, data from Fig. 8 can also be used to estimate indoor concentrations of $PM_{2.5}$ and total UFPs of outdoor origin on an absolute basis in each location, as shown in the cumulative distribution functions in Fig. 9. Estimates of $PM_{2.5}$ mass concentrations are made using the same assumptions for spherical particle shape and unit density as in Table 2. The predicted distributions of absolute indoor $PM_{2.5}$ and total UFP concentrations are also used alongside long-term time-averaged outdoor estimates (made using the same particle assumptions) to estimate infiltration factors for $PM_{2.5}$ and UFPs. The intent of this example is to explore sensitivity of the results to widely varying assumptions of outdoor particle size distributions.

According to Fig. 9a, time-averaged indoor $PM_{2.5}$ concentrations of outdoor origin are not predicted to vary greatly between each environment, although urban traffic areas are estimated to have higher indoor concentrations than urban or rural locations. The

Table 2
Lognormal characteristics of the ambient particle size distributions used in this study as representatives for typical rural, urban background, and traffic environments.

Location		Mode 1			Mode 2			Mode 3			Est. $PM_{2.5}$ mass	Total UFPs	Total N
		N_i	D_{pi}	$\log \sigma_i$	N_i	D_{pi}	$\log \sigma_i$	N_i	D_{pi}	$\log \sigma_i$	μg m^{-3}	# cm^{-3}	# cm^{-3}
		cm^{-3}	μm	–	cm^{-3}	μm	–	cm^{-3}	μm	–			
Rural	Mean	2200	0.014	0.30	2800	0.070	0.30	600	0.200	0.23	13.2	4204	5600
	s.d.	5000	0.011	0.28	2500	0.050	0.40	650	0.230	0.17	15.2	6944	8150
Urban background	Mean	2600	0.014	0.30	8200	0.048	0.36	700	0.170	0.20	15.0	9340	11500
	s.d.	3600	0.010	0.27	6200	0.048	0.36	600	0.170	0.20	11.8	8709	10400
Traffic	Mean	11500	0.013	0.24	10000	0.050	0.35	1400	0.150	0.18	17.5	19780	22900
	s.d.	13500	0.012	0.27	5000	0.050	0.35	1200	0.150	0.23	13.6	17787	19700

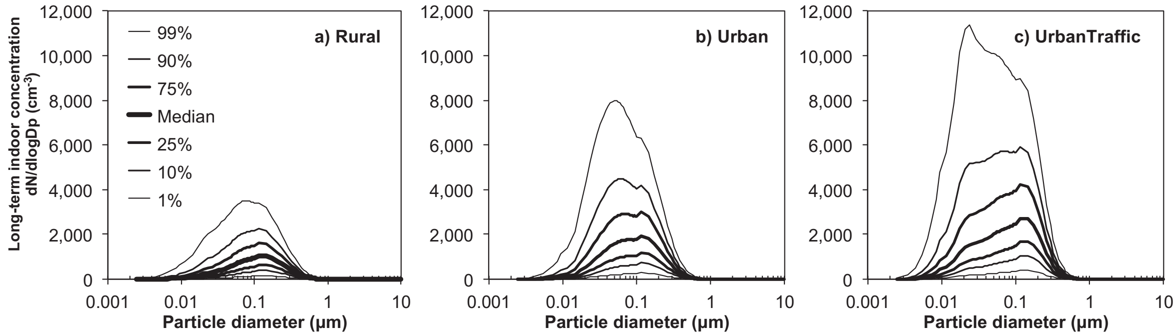

Fig. 8. Distributions of time-averaged indoor concentrations of outdoor particulate matter estimated using values of $F_{i,\text{inf}}$ from Fig. 5 and outdoor size distributions from Fig. 7. Estimates are made assuming all homes are located in (a) rural, (b) urban background, or (c) highly-trafficked urban locations.

median predicted indoor concentration of $PM_{2.5}$ of outdoor origin in the urban traffic environment is approximately 7 $\mu g/m^3$ compared to 5.8 $\mu g/m^3$ in the urban environment and 5 $\mu g/m^3$ in the rural environment. Conversely, absolute concentrations of UFPs are predicted to vary widely depending on environment, as shown in Fig. 9c. For example, if the median home is located in the urban traffic environment, time-averaged indoor UFP concentrations of outdoor origin would be ~1730 #/cm^3 compared to ~1070 #/cm^3 and ~460 #/cm^3 in the urban and rural locations, respectively (a factor of almost 4 between urban traffic and rural!). This difference in indoor concentrations is due to the large differences in outdoor UFP concentrations in each environment, as described in Table 2.

On the other hand, infiltration factors of both $PM_{2.5}$ and UFPs do not appear to be affected greatly by assumptions for outdoor particle size distributions (see Fig. 9b and d). Outdoor particle size distributions appear to have almost no impact on the cumulative distributions of $F_{i,\text{inf}}$ values for $PM_{2.5}$ while $F_{i,\text{inf}}$ values for UFPs are actually somewhat smaller for the urban traffic environment, most likely because a greater number of UFPs are smaller than 0.05 μm and predicted infiltration factors are less for <0.05 μm particles than for 0.05–0.1 μm particles (Fig. 6). While this analysis suggests that outdoor particle size distributions may not drastically affect infiltration factors for $PM_{2.5}$, which may be an important finding for informing future field studies, we should note that these results are limited in this example to our assumptions for both outdoor particle size distributions and particle shape and density. For instance, although we use a density of 1 g/cm^3 herein, other recent studies have shown that actual particles densities can range from 0.1 to

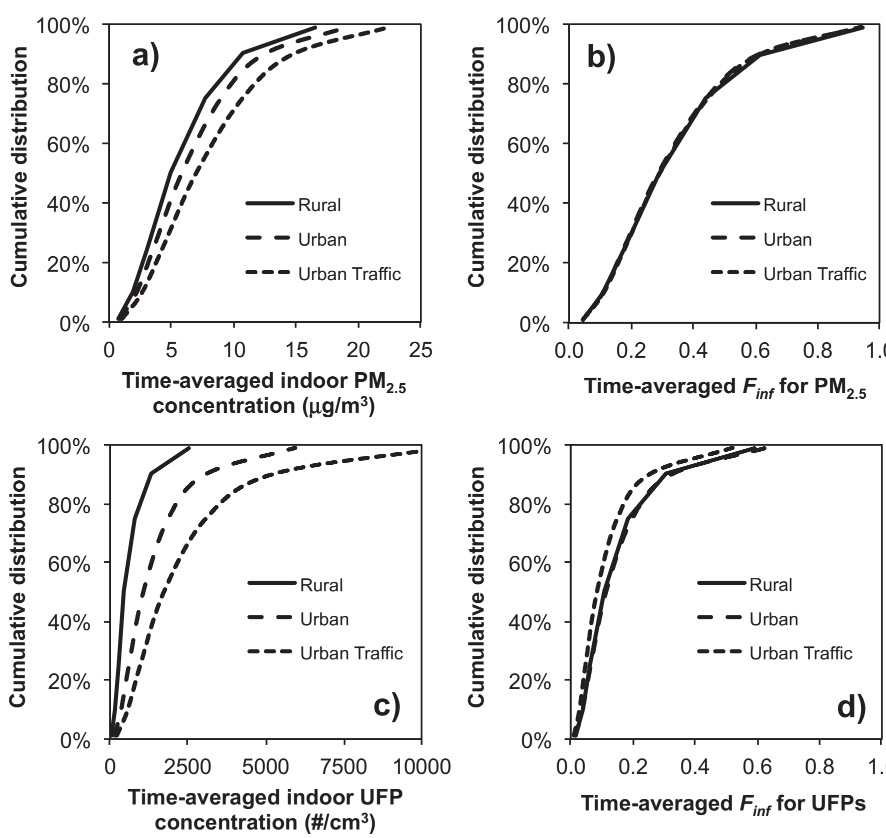

Fig. 9. Estimated cumulative distributions of (a) indoor $PM_{2.5}$ concentrations, (b) F_{inf} for $PM_{2.5}$, (c) indoor UFP concentrations, and (d) $F_{i,\text{inf}}$ for UFPs using the modeled indoor size distributions in Fig. 8 and assuming spherical particles with density of 1 g/cm^3 to estimate $PM_{2.5}$ mass.

2.5 g/cm^3, depending on geographic location and characteristics of nearby particle sources [81–87]. These impact of these assumptions could, however, be explored further using the size-resolved predictions of $F_{i,\text{inf}}$ in Fig. 5.

The predicted ranges of $F_{i,\text{inf}}$ values for both $PM_{2.5}$ and UFPs using this method are somewhat lower than most of the existing experimental data in homes. For example, we predict median $F_{i,\text{inf}}$ values for UFPs to range from ~0.08 to ~0.11, depending on outdoor particle size distributions, while median values for submicron particles (thought to largely represent UFPs) in Kearney et al. (2011) were ~0.19 to ~0.27, depending on season and estimation method [16]. Our predicted interquartile ranges (25th to 75th percentiles) of $F_{i,\text{inf}}$ for UFPs ranged from ~0.05 to ~0.20, depending on location, which was on the lower end of those observed in both [16] and [76]. Similarly, our predicted median values of $F_{i,\text{inf}}$ for $PM_{2.5}$ were approximately 0.28–0.29 depending on assumptions for outdoor size distributions, which is lower than typical medians or means ranging from ~0.35 to ~0.8 measured using several different methods across many different homes in both the U.S. and Canada [19,23,27,58,88,89]. However, our median estimates of $F_{i,\text{inf}}$ for $PM_{2.5}$ are very close to that measured in nearly 50 homes in Windsor, ON across multiple seasons [24]. However, we should note that there are many factors that lead to difficulty in providing a direct comparison to existing field studies, including typically limited sample sizes, durations, and locations in most of the existing field studies as well as limitations in our assumptions for particle size distributions and statistical distributions of input parameters.

3.3. Multiple regression analysis for influential parameters

In order to explore the most influential input parameters for predicting size-resolved infiltration factors in this model framework, this section summarizes results from a multiple linear regression on all 100,000 modeled values of $F_{i,\text{inf}}$ for each of the 102 particle size bins. Three separate regressions were performed, including (i) all results from the 100,000 simulated homes, (ii) only the results from the 35,000 simulated homes without HVAC systems, and (iii) only the results from the 65,000 simulated homes with HVAC systems. Seven model input parameters were used as predictor variables, including closed-window penetration factors ($P_{i,\text{closedwindows}}$), deposition rates ($k_{i,\text{dep,closedwindows}}$), and air exchange rates ($\lambda_{\text{closedwindows}}$); HVAC filter efficiency ($\eta_{i,\text{HVAC}}$); HVAC recirculation rate (λ_{HVAC}); HVAC system runtime (f_{HVAC}); and the fraction of time windows are open ($f_{\text{openwindows}}$). Only the closed-window values were used for the relevant input parameters because their time-averaged values are a function of another predictor variable ($f_{\text{openwindows}}$). The regression analysis followed the format in Equation (10).

$$F_{i,\text{inf}} = \beta_0 + \beta_1\lambda_{\text{closedwindows}} + \beta_2 f_{\text{openwindows}} + \beta_3 f_{\text{HVAC}} + \beta_4\lambda_{\text{HVAC}} + \beta_5\eta_{i,\text{HVAC}} + \beta_6 k_{i,\text{dep,closedwindows}} + \beta_7 P_{i,\text{closedwindows}} \quad (10)$$

To normalize and compare the strength of each predictor variable, we used the standardized regression coefficient (SRC), which is the actual regression coefficient (β_i) normalized by the ratio of the sample standard deviation of the dependent to independent variables [90]. SRCs can be interpreted as follows: (i) the (SRC)^2 estimates the relative variance contribution; (ii) a high |SRC| indicates a large influence, while an |SRC| near zero indicates no influence; and (iii) an input with a −SRC changes the $F_{i,\text{inf}}$ negatively and a +SRC changes $F_{i,\text{inf}}$ positively. Fig. 10 shows size-resolved SRCs for each predictor variable used in the regression analysis and Table 3 shows mean (±s.d.) values for the SRCs for all three regression analyses averaged across all particle sizes, ranked in descending order of influence. Finally, Fig. 11 shows the size-resolved model R^2 values for each regression.

Size-resolved closed-window deposition rates ($k_{i,\text{dep,closedwindows}}$) were shown to be the most influential parameter for predicting size-resolved infiltration factors in these simulations for all three regression analyses, explaining 28–42% of the variance among homes on average across all particle sizes (mean SRC of −0.56). Closed-window air exchange rates ($\lambda_{\text{closedwindows}}$) were the next most important predictor across all particle sizes for all three regression analyses, followed by closed-window envelope penetration factors ($P_{i,\text{closedwindows}}$). However, closed-window penetration factors had a slightly greater impact than closed-window AERs for some particle sizes in some subsets of homes (i.e., 0.1–0.5 μm particles in homes without HVAC systems). The importance of these three parameters is expected given their large ranges as inputs to the model. The influence of penetration factors is smallest for the smallest particles, most likely because the range of input values for particles less than ~0.02 μm is very small. SRCs for AERs and deposition rates do not vary as much by particle size because their ranges of input values also do not vary as much by particle size as penetration factors do. Unfortunately many of these assumptions cannot be explored further, as existing experimental data is quite limited.

HVAC filter removal efficiency ($\eta_{i,\text{HVAC}}$) was the next most important predictor for homes across all of the homes, as well as for those homes with HVAC systems. The fraction of time that windows are open ($f_{\text{openwindows}}$), HVAC system runtime (f_{HVAC}), and recirculation rates (λ_{HVAC}) were all only minor predictors for all three cases, with SRCs less than ±0.11, suggesting that the

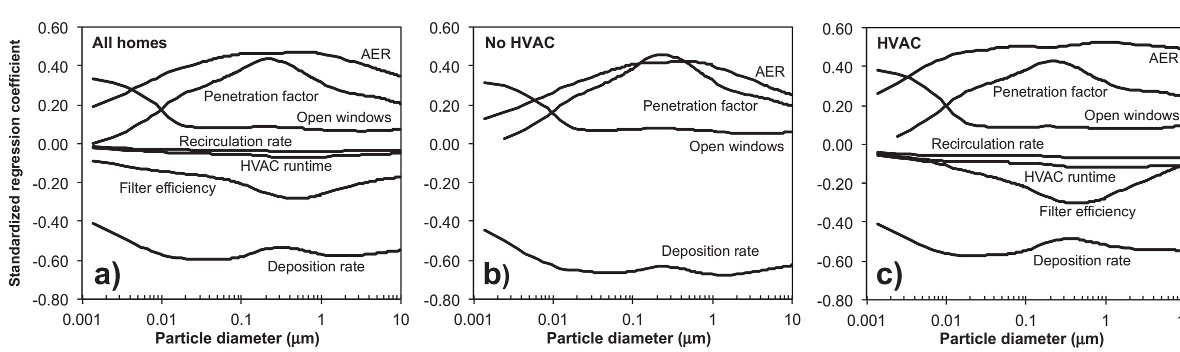

Fig. 10. Size-resolved standardized regression coefficients (SRCs) for predictor variables in multiple regression analyses: (a) all homes, (b) homes without HVAC systems, and (c) homes with HVAC systems.

Table 3
Mean ± standard deviation of the standardized multiple linear regression coefficients for each input variable for (i) all homes, (ii) only those homes without HVAC systems, and (iii) only those homes with HVAC systems.

Input parameter	Mean ± s.d. standardized regression coefficients (SRCs) across all particle sizes		
	All homes	No HVAC	HVAC
Closed-window deposition rate, $k_{i,\mathrm{dep,closedwindows}}$	−0.56 ± 0.03	−0.65 ± 0.03	−0.53 ± 0.03
Closed-window air exchange rate, $\lambda_{\mathrm{closedwindows}}$	0.42 ± 0.06	0.35 ± 0.07	0.49 ± 0.04
Closed-window penetration factor, $P_{i,\mathrm{closedwindows}}$	0.30 ± 0.09	0.30 ± 0.10	0.31 ± 0.08
HVAC filter efficiency, $\eta_{i,\mathrm{HVAC}}$	−0.21 ± 0.05	Omitted	−0.20 ± 0.07
Fraction of time windows are open, $f_{\mathrm{openwindows}}$	0.09 ± 0.05	0.08 ± 0.05	0.11 ± 0.06
HVAC system runtime, f_{HVAC}	−0.06 ± 0.01	Omitted	−0.10 ± 0.01
Recirculation rate, λ_{HVAC}	−0.04 ± 0.00	Omitted	−0.06 ± 0.01

contribution to the variance of the results was less than 1.2% (or 0.11^2). However, window opening was a greater predictor for the smallest UFP sizes (i.e., <0.01 μm), explaining as much as ∼15% of the variance for very small particles. This is intuitive, as open windows will have a large relative influence on the very small closed-window penetration factors for the smallest particles.

Each parameter was also found to influence infiltration factors in a logical manner; that is, deposition rates (a loss term) were negatively associated with values of $F_{i,\mathrm{inf}}$, while penetration factors (a source term) were positively associated with values of $F_{i,\mathrm{inf}}$. These results suggest that in order to better estimate size-resolved infiltration factors in field studies and to incorporate into future epidemiological studies, accurate characterization of size-resolved deposition rates, closed-window air exchange rates, and size-resolved envelope penetration factors should be prioritized, followed by size-resolved HVAC filter efficiencies for homes with HVAC systems and window opening behaviors for homes without HVAC systems. Although we are aware of large datasets for residential air exchange rates, information is particularly lacking on size-resolved deposition rates, size-resolved envelope penetration factors, and in-situ HVAC filter efficiencies across the wide range of particle sizes considered herein.

Values for the coefficient of determination (model R^2 values) ranged from 0.32 to 0.77 depending on particle size, suggesting the multiple regressions predict size-resolved infiltration factors for some particle sizes better than others across all modeled homes. The mean (±s.d.) R^2 value was 0.65 ± 0.11 across all particle sizes, with the highest values associated with 0.1–1 μm particles, perhaps because there are mostly nonzero values associated with size-resolved input parameters for this size range. Model R^2 values were also generally higher for the regression analysis using only the homes with HVAC systems, which suggests that the range of inputs used herein can better predict size-resolved infiltration factors in homes with central HVAC systems and filters.

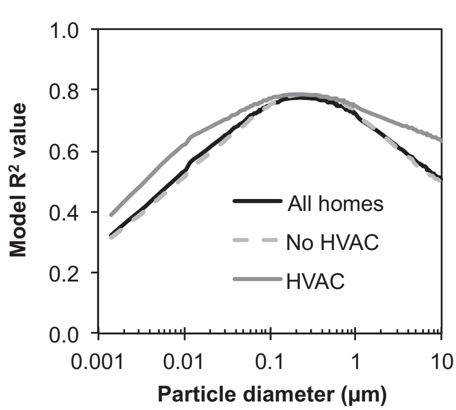

Fig. 11. Model R^2 values for the multiple linear regressions for each particle size.

4. Implications and limitations of this work

Overall, results from the application of the model framework and Monte Carlo simulations herein using best available data for important input parameters suggest that indoor proportions of outdoor size-resolved particles, UFPs, and $PM_{2.5}$ can vary widely among homes due to wide ranges of fundamental, influential building characteristics, which is consistent with limited experimental data in the literature. Importantly, this wide variability in size-resolved infiltration factors among U.S. residences should be accounted for in future epidemiological studies to limit exposure misclassification. Additionally, measured data for a number of key input parameters that could be used in similar size-resolved modeling efforts to improve epidemiology studies are severely lacking, and this work helps to prioritize measurements of a number of important parameters and building characteristics that govern outdoor particle infiltration in residences.

However, we should also note that there are several important limitations to this work. For one, actual measured values of both size-resolved envelope penetration factors and particle deposition rates remain very limited. More research should measure size-resolved particle penetration factors and deposition rates across the widest size range possible and in a larger number and variety of residential buildings. Results from the multiple linear regressions confirm the importance of both of these variables, as well as the importance of accurately assessing air exchange rates. Additionally, data for HVAC system runtimes, size-resolved filter efficiencies, filter ownership, window opening behaviors, and AERs during window opening all remain limited and warrant further study.

We should also note that there might be considerable uncertainty in the shape of the outdoor particle size distributions we used in the latter portion of this analysis. More information is needed on long-term time-averaged outdoor particle size distributions in urban, rural, and highly trafficked urban environments in the U.S. to fully explore the impacts of outdoor size distributions. Moreover, the particle number balance in Equation (1) ignores other loss mechanisms such as loss of particles by partitioning of semivolatile compounds (e.g., for organic nitrate particles or secondary organic aerosols), which can alter indoor size distributions and mass concentrations [12,30,33,91,92]. However, the wide range in deposition rates used herein should capture much of the variability that would be introduced by particle volatility. Additionally, this work focused on infiltration factors and explicitly ignores indoor sources of particles. There are many indoor sources of a wide range of particle sizes inside homes that lead to significant exposure [93,94]. Further modeling should incorporate size-resolved source strengths and time activity patterns.

Regardless, results herein demonstrate the utility of this model framework and suggest that wide variations in indoor particle concentrations (and thus exposures) exist across the U.S. residential building stock. Additionally, these variations may be predicted with some confidence by differences among home characteristics, which should be accounted for in epidemiological studies. Although more information is needed on a wide range of fundamental building-related input parameters, the modeling framework described herein can also be used to incorporate new data as they are revealed or to explore hypothetical changes to the building stock, such as widespread decreases in AERs due to weatherization or increases in ownership of higher-efficiency HVAC filtration.

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