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Estimating Climate Change-Related Impacts on Outdoor Air Pollution Infiltration

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Abstract

Background.—Rising temperatures due to climate change are expected to impact human adaptive response, including changes to home cooling and ventilation patterns. These changes may affect air pollution exposures via alteration in residential air exchange rates, affecting indoor infiltration of outdoor particles. We conducted a field study examining associations between particle infiltration and temperature to inform future studies of air pollution health effects.

Methods.—We measured indoor fine particulate matter ($PM_{2.5}$) in Atlanta in 60 homes (810 sampling-days). Indoor-outdoor sulfur ratios were used to estimate particle infiltration, using central site outdoor sulfur concentrations. Linear and mixed-effects models were used to examine particle infiltration ratio-temperature relationships, based on which we incorporated projected meteorological values (Representative Concentration Pathways intermediate scenario RCP 4.5) to estimate particle infiltration ratios in 20-year future (2046–2065) and past (1981–2000) scenarios.

Results.—The mean particle infiltration ratio in Atlanta was 0.70 ± 0.30, with a 0.21 lower ratio in summer compared to transition seasons (spring, fall). Particle infiltration ratios were 0.19 lower in houses using heating, ventilation, and air conditioning (HVAC) systems compared to those not using HVAC. We observed significant associations between particle infiltration ratios and both

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Credit Author Statement

D.L., P.K., and J.S. designed the research and directed its implementation; D.L., WC.L., J.L., S.E., CM.K., and J.W. prepared datasets; D.L., WC.L., and J.L. analyzed data; D.L., P.K., and J.S. wrote the paper and made the tables and the figures; and all authors contributed to the revision of the manuscript.

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linear and quadratic models of ambient temperature for homes using natural ventilation and those using HVAC. Future temperature was projected to increase by 2.1 °C in Atlanta, which corresponds to an increase of 0.023 (3.9%) in particle infiltration ratios during cooler months and a decrease of 0.037 (6.2%) during warmer months.

Discussion.—We estimated notable changes in particle infiltration ratio in Atlanta for different 20-year periods, with differential seasonal patterns. Moreover, when stratified by HVAC usage, increases in future ambient temperature due to climate change were projected to enhance seasonal differences in $PM_{2.5}$ infiltration in Atlanta. These analyses can help minimize exposure misclassification in epidemiologic studies of $PM_{2.5}$, and provide a better understanding of the potential influence of climate change on $PM_{2.5}$ health effects.

Keywords

Climate change; Indoor-outdoor sulfur ratio; Temperature; Particle infiltration

Introduction

The impact of both short- and long-term exposures to fine particulate matter ($PM_{2.5}$) on the global burden of disease has been well established (Cohen et al. 2005; WHO 2016; Cohen et al. 2017). Individual exposure to $PM_{2.5}$ can vary considerably, and is subject to modification from physical, behavioral, and socio-demographic factors. Notably, most individuals spend the majority (>90%) of their time indoors (Klepeis et al. 2001), and exposure to $PM_{2.5}$ also occurs for many people during transportation and at work (Meng et al. 2005). Home ventilation has been identified as a central driver of indoor $PM_{2.5}$ levels (Thatcher and Layton 1995; Liu and Nazaroff 2003). Specifically, home ventilation affects indoor $PM_{2.5}$ levels through its competing influence of outdoor ambient particle infiltration and exfiltration of indoor-generated particle sources (Long et al. 2001).

Ventilation is commonly expressed in terms of air exchange rate (AER), or the number of times an indoor air volume is replaced by outdoor air over time (*e.g.*, per hour). Limited previous studies have suggested that AER may modify both short- and long-term health risks of air pollution (Janssen et al. 2002; Bell and Dominici 2008; Sarnat et al. 2013). The observed association of outdoor $PM_{2.5}$ health effects with AER may be due, in part, to its impact on total human exposure to particles from outdoor sources.

Broadly, AER is associated with building envelope tightness and other aspects of physical structure, as well as several key meteorological factors, including ambient temperature and wind speed (Chan and Gadgil 2005; Sherman and Chan 2006; Persily et al. 2010). Given the influence of meteorology on AER, projected changes in ambient temperature associated with long-term global climate trends may affect population exposures to $PM_{2.5}$ and their related disease burden. To our knowledge, only a few limited studies have examined this to date (Ilacqua et al. 2017; Lee et al. 2017). Using the Lawrence Berkeley National Laboratory model of infiltration and climate change data in nine metropolitan areas in the United States, Ilacqua et al. reported that infiltration associated with AER would decrease by 5% due to climate change, while localized increased infiltration is expected during the summer months, up to 20–30% (Ilacqua et al. 2017). In a retrospective cohort 340 homes in the greater

Boston area, our group modeled increased future temperatures due to climate change to be associated with increased $PM_{2.5}$ infiltration, particularly during the summer (Lee et al. 2017). These earlier analyses left some major questions concerning the generalizability of their findings to other locales, and incompletely characterized uncertainty resulting from using simulation analysis and retrospective databases.

To address these gaps, we conducted this study with the aim of quantifying the change of AER due to temperature increases resulting from climate change, and assess its impact on $PM_{2.5}$ exposure. We hypothesized that future outdoor temperature increases would alter the contribution of outdoor particle sources to indoor concentrations, leading to differences in $PM_{2.5}$ infiltration. To test this hypothesis, we conducted a large field sampling study consisting of 60 single family homes (each household with 14 exposure-days conducted in both warm and cold seasons) in the greater Atlanta area to model the relationship between outdoor temperature and $PM_{2.5}$ infiltration. To estimate $PM_{2.5}$ infiltration, we use sulfur ratio (S_r) as a tracer of outdoor $PM_{2.5}$ infiltration into the indoor environment. As a major constituent of $PM_{2.5}$, sulfur is a chemically stable pollutant, with few indoor sources, and negligible spatial variability over the region of greater Atlanta, with infiltration and deposition rates similar to those of $PM_{2.5}$ (Sarnat et al. 2002). Thus S_r has been accepted as a means of approximating outdoor $PM_{2.5}$ infiltration ratios in numerous studies and reviews (Sarnat et al. 2002; Diapouli et al. 2013; Breen et al. 2014; Lee et al. 2017). Using modeled projected temperature increase derived from Intergovernmental Panel on Climate Change (IPCC) climate change models to predict future particle infiltration ratio (2046–2065) as well as historic particle infiltration ratio (with 1981–2000 as a control), we modeled the impact of temperature increases on $PM_{2.5}$ infiltration in Atlanta. Results from this current analysis are expected to test the generalizability of our previous findings and fill knowledge gaps in population-based particle infiltration studies, providing a tool for future investigations on potential influence of climate change on $PM_{2.5}$ health effects.

Methods

Study Population and Field Campaign

We conducted a prospective field sampling campaign in Atlanta between January 2016 and June 2017. During this period, 60 single-family residences, with non-smoking residents, were recruited from the Atlanta metropolitan area. Home measurements were made using a convenient sampling method. While home selection was not random or generalizable, the homes in the study varied by size, age, architectural style, and geographic location within the city. Indoor air sampling in each household was scheduled for two sessions, during both cool and warm months, for periods of 7 consecutive days in each session. In addition, a questionnaire was completed for each home for home type, age, and size, as well as for indoor emission sources that may impact $PM_{2.5}$ and sulfur levels, such as cooking, wood stoves, and candles. In addition, questions regarding parameters influencing home air exchange rates were included, such as use of heating, ventilation, and air conditioning (HVAC), and the frequency of opening windows. Indoor temperature and relative humidity were measured using the HOBO Temperature/Relative Humidity 3.5% Data Logger (Onset Inc). Fifty-seven of 60 (95%) households participated in both sessions, while three households were lost to follow up at the second visit. The study protocol was approved by the Institutional Review Board of Emory University. All participants provided informed written consent.

Exposure Assessment

For each field session, $PM_{2.5}$ was collected on 37 mm Teflon filters every 24 hours using a custom-made sampling manifold, which we successfully deployed in previous studies (Zanobetti et al. 2014). The sampler was placed in the main activity room (other than kitchen), typically the family or living room. The sampler started automatically when plugged in and was unplugged immediately at the end of the sampling period. The average flow rate of the sampler was set at 4 L/min. All indoor filters were analyzed for $PM_{2.5}$ mass gravimetrically and for trace elemental concentrations (including sulfur) using X-Ray Fluorescence (XRF) at the Harvard T.H. Chan School of Public Health (Lee et al., 2017).

Concentrations of corresponding 24-hour outdoor $PM_{2.5}$ and sulfur concentrations were measured at the Jefferson Street monitoring site (JST), which has been used previously to generate population exposure estimates in various air pollution health studies conducted in Atlanta (Sarnat et al. 2013; Strickland et al. 2010; Liang et al. 2018b; Sarnat et al. 2018; Liang et al. 2019; Blumberg et al. 2020; Li et al. 2021) and is generally considered to be representative of Atlanta urban background pollutant concentrations and composition (Solomon et al. 2003; Liang et al. 2018a; Moutinho et al. 2020). In this study, daily particle infiltration ratio in each household was determined as the ratio of sulfur concentration measured indoors to the concurrent measured concentrations from JST. The same approach was previously reported to show good agreement with independently validated indoor-outdoor $PM_{2.5}$ ratios in six Boston homes (Sarnat et al. 2002) and has been used widely in the field (Wallace and Williams 2005; Lee et al. 2017).

Prior to, during, and after the field sampling, we conducted quality assurance and quality control by running 4 independent sessions of side-by-side collocated measurements. A total of 80 samples were collected and analyzed. The precision in measuring sulfur concentrations was excellent, with an average relative precision of 7.6%. We also compared the samplers with two different outdoor monitoring sites (including the central monitoring JST site) and observed a relative precision of 4.1%. In addition, 54 field and lab blanks were collected during the field campaign. The blanks for PM mass did not significantly differ from zero, but the blank sulfur mass concentrations averaged 0.0011 ± 0.0012 μg/m^3 and sample concentrations were corrected accordingly.

Meteorology Data

We obtained representative meteorology data for the homes in our study cohorts from the North American Regional Reanalysis (NARR) database, which provides historical high resolution data for North America based on 32×32 km geographical grid (Mesinger et al. 2006). The metropolitan area of Atlanta overlaps with 36 geographical grids in NARR database. Home locations were matched to the centroids of the grids from the NARR database, where meteorology data from the grid with the smallest distance to a home was used to provide representative weather data for the home, including average daily temperature (measured at 2 m above the surface), wind speed (measured at 10 m above the surface), and precipitation and relative humidity (measured at 2 m above the surface). We replaced negative values for precipitation by zero. This approach was used to minimize potential bias resulting from spatial variability on the observed association between meteorology and particle infiltration ratio, as compared with using data measured from the Atlanta Hartsfield-Jackson International Airport site.

Climate forecast model

We modeled daily meteorological variables, including temperature, wind speed, relative humidity, and precipitation in Atlanta for two analytic 20-year periods: 1981–2000 (past) and 2046–2065 (future). The modeled past predictions between 1981 and 2000 were used to compare with future climate-change induced temperature changes generated by the same model, so that both sets of predictions exhibited similar uncertainties and potential biases. Modeled parameter values for both the past and future periods were generated using data archived for the Coupled Model Inter-comparison Project Phase 5 (CMIP5), an initiative of the Intergovernmental Panel on Climate Change Fifth Assessment Report (Stocker et al. 2013). This database contains projected meteorology generated by a suite of climate models for a range of socioeconomic scenarios, known as the Representative Concentration Pathways (RCPs), labelled for potential radiative forcing in the year 2100 of 8.5 W/m^2 (RCP8.5), 6.0 W/m^2 (RCP6.0), 4.5 Wm^{-2} (RCP4.5), and 3 Wm^{-2} (RCP2.6). We chose the RCP4.5 intermediate scenario in this analysis and obtained projected daily values for 6 weather variables in Atlanta for the periods between 1981–2000, and 2046–2065, including temperature (K), wind speed (m/s), relative humidity (%), precipitation (kg/m^2/day), pressure at mean sea level (Pa), and specific humidity (kgwater/kgair), from an ensemble of 14 CMIP5 models, which have a horizontal resolution of ~200 km.

To compare the CMIP5 historical data to the actual weather records for data quality assurance, we matched Atlanta zip code centroids to the nearest NARR grids for data extraction. Atlanta overlaps with 36 NARR grids; therefore, we averaged the values of the selected 6 weather variables over these 36 grids to give the final daily data for 1981–2000 in the NARR dataset. To correct bias in the CMIP5 meteorology data, we calculated the daily bias between projected meteorological variables in CMIP5 and those in NARR during the period of 1981–2000. Then we subtracted the daily bias of each variable from the original CMIP5 archives for 1981–2000 and 2046–2065. Finally, we processed these bias-corrected meteorological variables into daily averaged values and subsequently used statistical analysis to predict particle infiltration ratios for the past and the future 20-year analytic period.

Data analysis

We conducted descriptive statistics for indoor and outdoor $PM_{2.5}$ and sulfur concentrations, indoor-outdoor particle infiltration ratios (i.e. S_r) (in all homes, and stratified by HVAC use), and meteorology parameters.

First, to test the hypothesis whether particle infiltration ratio was a function of outdoor temperature, we modeled particle infiltration ratio as a function of temperature using data collected in all 60 houses in Atlanta during 2016–2017. Based on a previous finding (Lee et al. 2017), we expected HVAC usage would modify the temperature effect on particle infiltration ratio, largely due to reduced air exchange rate on closed window days, and increased air exchange rate when HVAC was not used and windows were opened for ventilation. Consequently, these models were conducted using: 1) all homes (the entire population) with mixed HVAC usage (HVAC=mixed), and; 2) homes stratified by HVAC usage, (i.e., the subpopulation of naturally ventilated homes with no HVAC usage (HVAC=0) and the subpopulation of homes with HVAC usage (HVAC=1). Window opening status was highly correlated with HVAC usage and was thus not included in the analysis (Lee et al. 2017). Linear mixed effect models were conducted to examine the association between particle infiltration ratio and outdoor temperature for all three population scenarios, while controlling for a random home-specific intercept to account for the autoregressive residual correlation from the repeated measurements within the same home and the heterogeneity of the overall particle infiltration ratio between homes. Daily averages of each of the other meteorological parameters, including wind speed, relative humidity and precipitation, and household physical factors, such as house age, square footage, and number of window, were used first in separate models to test their individual associations as predictors of particle infiltration ratio. Where significant, these independent terms were also included as covariates in the final multivariate particle infiltration ratio-temperature model.

To test whether variation in the future *versus* past ambient temperatures alter $PM_{2.5}$ infiltrations and corresponding contributions to indoor concentrations by month, we estimated past and future particle infiltration ratio using our particle infiltration ratio-temperature model outlined above, in conjunction with projected meteorology for 1981–2000 and 2046–2065 periods. Daily meteorology predictions were summarized into monthly or yearly averages based on individual CMIP5 models. To account for variability in predictions across all CMIP5 models, predictions were presented as the overall mean ± standard deviation (SD).

All statistical analyses were performed in R, version 3.4 (R Foundation for Statistical Computing; http://www.r-project.org/). Effect estimates with p-value ≤0.05 were considered significant.

Results

We collected 810 24h-integrated indoor samples from 60 homes across all 12 calendar months in the Atlanta Metropolitan area between January 2016 and June 2017. The average indoor $PM_{2.5}$ and sulfur concentrations were 10.2 ± 15.8 $\mu g/m^3$ and 0.3 ± 0.2 $\mu g/m^3$, respectively, while the average outdoor $PM_{2.5}$ and sulfur concentrations, measured at the JST central monitoring site, were 10.9 ± 4.7 $\mu g/m^3$ and 0.4 ± 0.2 $\mu g/m^3$, respectively. Summary statistics for other sampling parameters, meteorology factors, and household characteristics collected from the baseline questionnaire are presented in Table 1 and supplementary Table S1. During the study period, the average ambient and indoor temperatures were 18.4 ± 7.5 and 22.2 ± 2.4 °C, respectively.

Using the outdoor sulfur concentrations measured at the JST monitoring site as an indicator of ambient sulfur across the sampling domain, mean indoor-outdoor particle infiltration ratio (i.e. S_r) for these homes was 0.74 ± 0.39 (i.e. 74% of outdoor $PM_{2.5}$ infiltrates indoors). There was a clear seasonal trend in particle infiltration ratio during the study period, where homes measured during transition seasons (February to April, and October to November) exhibited higher mean particle infiltration ratio as compared to homes measured during summer and winter months (Figure 1). When stratified by HVAC usage, mean particle infiltration ratio in naturally ventilated homes was 0.79 ± 0.30 (N=539), comparable, albeit moderately higher, than mean particle infiltration ratio in homes using HVAC (0.72 ± 0.44, N=271) (Table 1, Figure 2). Among the modeled meteorological variables, ambient temperature was the only statistically significant predictor of particle infiltration ratio, where a 1 °C increase in temperature was associated with a 1.2% decrease (0.009) in particle infiltration ratio (Table 2). Indoor temperature and indoor relative humidity were both significantly associated with particle infiltration ratio. Since the climate model cannot predict indoor meteorological parameters, we only used outdoor temperature as a predictor of particle infiltration ratio in the statistical analysis. Many household physical characteristics, including house age, square footage, and number of windows, were not associated with particle infiltration ratio in the model, and were thus not included in the final statistical model (Table 2 and Figure S1).

We observed substantial variability in particle infiltration ratio across the different homes, with 17% of samples yielding particle infiltration ratio >1, indicative of potential indoor sulfur sources (Figure S2). Given that the key underlying assumption of using sulfur ratio as a surrogate of $PM_{2.5}$ infiltration factor is the absence of indoor sources of sulfur, to minimize misclassification, we assembled a reduced, censored dataset which excluded 138 sampling days with particle infiltration ratio >1. Moreover, 23 additional samples from 5 households were excluded in the reduced dataset due to over 70% of the measured particle infiltration ratio >1. A total of 810 and 649 samples were used in the full and reduced dataset, respectively, for the statistical analysis.

We observed significant associations between particle infiltration ratio and outdoor temperature in the full dataset, modeling temperature as a both a linear and quadratic term (Table 3). Specifically, in the quadratic models, particle infiltration ratio was positively associated with temperature in lower temperature ranges (<18 °C), with the particle infiltration ratio-temperature association turning negative in higher temperature ranges (>18 °C). Consistent quadratic trend in particle infiltration ratio-temperature association was observed in models stratifying homes by use of HVAC.

We observed similar trends in both the full and reduced datasets (Table 3). For the reduced dataset, both linear and quadratic forms of outdoor temperature were significantly associated with particle infiltration ratio in all three scenarios (i.e. AC=mixed, 0 or 1). Thus, we used the effect coefficient estimates of the linear and quadratic forms of outdoor temperature in the reduced dataset to predict particle infiltration ratio using the estimated past and future temperatures from an ensemble of 14 CMIP5 models.

We present the 20-year averages of monthly mean temperature under the RCP 4.5 intermediate scenario for the past and future study periods from all 14 CMIP5 models and their overall monthly averages in Figure 3. We observed good predictability for temperature among these CMIP5 models, where the model-specific trends and monthly temperature prediction were consistent. In the future period, mean monthly temperature is projected to increase by 1.5–2.5°C in Atlanta relative to the past period, with larger temperature increases predicted during summer months (Figure 3). Correspondingly, this would result in a 0.023 ± 0.008 (3.9%) increase in particle infiltration ratio (i.e., increased outdoor infiltration) during cooler months (October to March), and an average 0.037 ± 0.015 (6.2%) decrease during warmer months (April to September, Figure 4C). The predicted seasonal trends of particle infiltration ratio in the past (1981–2000) and in the future (2045–2065) were also consistent with the current seasonal trend observed for the field study, when transition season had higher particle infiltration ratio and summer had lower infiltration due to the high prevalence of AC usage (Figures 4A and 4B).

When stratified by HVAC usage, increased future climate change-related temperatures were projected to enhance seasonal differences in $PM_{2.5}$ infiltration in Atlanta (Figure 5). In 20 years, seasonal difference (between transition season and summer) in mean particle infiltration ratio was estimated to be as high as 0.22 (45.7%) for naturally ventilated homes (HVAC=0) and 0.15 (27.8%) for the whole population (HVAC=mixed), using summer as a baseline reference (Figure 5B). A similar profile was observed for the past period, with less substantial seasonal differences. Mean particle infiltration ratio was estimated to be 0.13 (22.3%) and 0.09 (14.9%) higher during transition season compared to summer for naturally ventilated homes and homes with HVAC usage, respectively.

Discussion

We conducted this large prospective study of 60 single-family residences to investigate the impact of temperature increases due to projected climate change on outdoor $PM_{2.5}$ infiltration in Atlanta. The current analysis is particularly pertinent to public health since people spend 90% of their time indoors. Increasing ambient temperatures due to climate change can, correspondingly, lead to changes in infiltration patterns, thus affecting our exposure to ambient air pollution and associated adverse health effects. To our knowledge, this study constituted the single largest prospective, longitudinal assessment on the relationship between daily and long-term temperature change and particulate pollutant infiltration.

Broadly, the results during this two-year study point to a substantial impact of outdoor temperature on particle infiltration ratio and changes in future particle infiltration ratio due to climate change, modified further by changes in HVAC usage. Based on these measurements and analyses, we offer several key findings to potentially help provide a better understanding of the influence of projected climate change on $PM_{2.5}$ health effects.

There are previous reports that outdoor temperature has a strong impact on particulate matter infiltration, mainly by changing residential frequency of HVAC usage and window opening (Wallace et al. 2002; Kearney et al. 2014). However, our study confirms the effect of outdoor temperature, and indicates that other meteorological parameters play a negligible role. In general, particle infiltration has been reported to be higher with frequent window opening for natural ventilation, and lower with HVAC in use and windows closed (Howard-Reed et al. 2002; Wallace et al. 2002; Howard-Reed et al. 2003). Our analysis is consistent with these findings, since we observed a strong association between outdoor temperature, HVAC usage, and frequency of window opening. In Atlanta, there were more than 95% households using HVAC in the summer and winter seasons (June to September and December to January, respectively). The frequency of window opening was highest during the two transition seasons (April to May and October to November), when HVAC is not necessary. Using sulfur ratio as a surrogate of particle infiltration, we observed lower particle infiltration ratio values during the summer or winter likely due to greater HVAC usage, and substantially higher particle infiltration ratio values during the transition seasons, when people tend to open windows frequently as a means of ventilating their homes. The particle infiltration ratio seasonal trend observed here was robust across the past and predicted future trends.

A limited number of studies have examined the relationship between temperature profiles and particle infiltration. Hystad et al. conducted indoor and outdoor light scattering measurements of PM from 84 homes in two cities in North America and observed a significant positive linear relation between outdoor temperature and $PM_{2.5}$ infiltration (Hystad et al. 2009). In the Multi-Ethnic Study of Atherosclerosis and Air Pollution (MESA Air), 2-week average outdoor temperature was the most consistent predictor of particle infiltration, with a positive linear association during the cold season (Allen et al. 2012). However, the generalizability of these findings is somewhat limited due to the relatively small sample size and that not all seasons of the year were sampled. Notably, our results show significant non-linear particle infiltration ratio-temperature associations, which were positive when temperatures were lower (<18 °C), and negative with steep rates of change when temperatures were higher. Using daily average temperature as a continuous predictor for particle infiltration ratio with a nonlinear model, we were able to overcome the above limitations and investigate the particle infiltration ratio-temperature relationship with a finer temporal coverage and more accurate assessment. This finding is supported by results from two previous studies that quantified the relationship between continuously measured temperature and particle infiltration (Meng et al. 2009; Lee et al. 2017). Meng et al., for example, reported greater particle infiltration for homes without AC, and a non-linear relationship where the highest infiltration occurred at 20°C across 114 homes from 3 cities using 48-hour integrated samples.

Our findings are also consistent with a similar study we conducted in 340 homes in the greater Boston area (Lee et al. 2017), where temperature was found to be the only significant predictor of particle infiltration ratio among all meteorological variables in homes with or without AC usage. However, compared to the positive linear and quadratic relationships between temperature and particle infiltration ratio observed in Boston, the temperature-particle infiltration ratio association observed in Atlanta exhibited a different pattern. Specifically, the quadratic term of temperature was negatively associated with particle infiltration ratio, indicating that particle infiltration ratio would decrease substantially for lower or higher temperature ranges. We hypothesize that the observed different patterns between Atlanta and Boston mainly resulted from their distinct climate patterns, where Atlanta has hotter summers and milder winters compared to Boston. Substantial differences in HVAC prevalence and usage also exist between these cities. Strikingly, in Atlanta, 79% of the households sampled used HVAC throughout the year, compared to 24.3% HVAC usage for the homes in the Boston study. For most households in Atlanta operating HVAC during summer and winter, particle infiltration ratio decreased substantially in both lower and higher temperature ranges, correspondingly.

Using this particle infiltration ratio-temperature relation together with the estimated past and future temperature from an ensemble of 14 CMIP5 models, we predicted a 3.9% increase in particle infiltration ratio during cooler months and an average 6.2% decrease during warmer months in Atlanta, where enhanced seasonal differences in $PM_{2.5}$ infiltration would be observed among naturally ventilated households without HVAC usage. Generally, the difference was smaller for the past than predicted for the future because particle infiltration ratio in naturally ventilated homes is expected to be more sensitive to increasingly higher temperatures in the future. The predicted 45.7% difference in particle infiltration ratio between transition season and summer for naturally ventilated homes in the future 20 year-period suggests that this subpopulation may be more vulnerable to ambient air pollution with the corresponding enhanced infiltration of outdoor particles during transitions. Thus, added caution and targeted preventive action (i.e. use of air filtering, alternative ventilation mechanisms, or personal protection equipment) may be recommended with the goal of protecting those most susceptible.

It is important to emphasize several key assumptions in our analysis. In conducting the study, we assumed that individuals would react and behave to changing temperature conditions in a similar way during both analytic periods. This *status quo* response implies that individuals will adapt to climate changes by opening windows more (when temperatures are moderate) or use more air conditioning (when temperatures are hot). However, humans could, and perhaps will, assimilate to a changing climate, by moving to areas less impacted by these changes or by adopting behaviors and responses different from those practiced today. We believe, however, that behavioral adaptations are less likely to occur if temperature in a city changes slowly over many years by only 2–3 °C (Lee et al. 2017). In addition, we assume that homes in the future will be constructed and operated in the same manner as they are today. It is possible, however, that homes will be more efficiently insulated, influencing corresponding patterns of window usage as well as general heating and cooling practices. The HVAC system used to heat or cool homes may also change in the future, and the rate of technology penetration will depend on the cost and affordability. Despite this, it is worth reiterating that the lifespan of homes can vary from a few decades to 100 or more years, suggesting that it may take a long time to replace housing stock. Since the average temperature is modeled to change by a few degrees with a few additional episodes of high temperature conditions, our assumption that we will overcome climatic changes simply by using more AC in the summer and open the windows more during the transition seasons seems reasonable. These behavior changes have the potential to substantially impact home ventilation, and as a result, the contribution of indoor and outdoor sources to total indoor $PM_{2.5}$. In this analysis, we studied the impact of changes in average temperature and observed notable changes on future particle infiltration; however, changes in minimum and maximum temperature in the future will be larger and therefore may have a greater impact on particle infiltration.

In addition, some limitations of this analysis warrant attention. The generalizability of the observed study findings may be limited and may not apply to other cities with differences in climate conditions, housing characteristics and occupant behaviors, as demonstrated by the differential particle infiltration ratio-temperature relation observed in Atlanta compared to that previously reported in Boston (Lee et al. 2017). Future study should consider using sampling sites from various regions with different climate patterns. In assessing the relationship between different meteorological factors and particle infiltration ratio, indoor temperature and relative humidity also can be assumed to be significantly associated with particle infiltration ratio, but were not included in the final statistical analyses due to the lack of climate change predictions for indoor environments. It is possible that indoor temperature and relative humidity may change substantially in the future and thus exert different influences on particle infiltration, which we are not able to predict in the current analysis. Finally, although we use temporally resolved measurements (24 hour-sampling), and recorded participant activity and household physical characteristic with a daily questionnaire, it is possible that other unknown or unquantifiable factors may influence infiltration. When conducting our sensitivity analyses using the reduced dataset, which excluded households with potential indoor sulfur sources (N=138), we observed similar, consistent particle infiltration ratio-temperature associations compared to results from the full dataset.

Under a mild climate change scenario, we quantified the temperature and particle infiltration ratio relationship, and predicted changes in particle infiltration due to predicted future increases in temperature. These analyses can help provide a better understanding of the potential influence of climate change on $PM_{2.5}$ health effects.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Highlights

- To date, largest prospective, longitudinal assessment of temperature change and particulate pollutant infiltration
- Temperature significantly associated with ambient particle pollution infiltration indoors
- Climate changes projected to enhance seasonal differences in particle infiltration
- Stronger increase in future particle infiltration projected among naturally ventilated houses

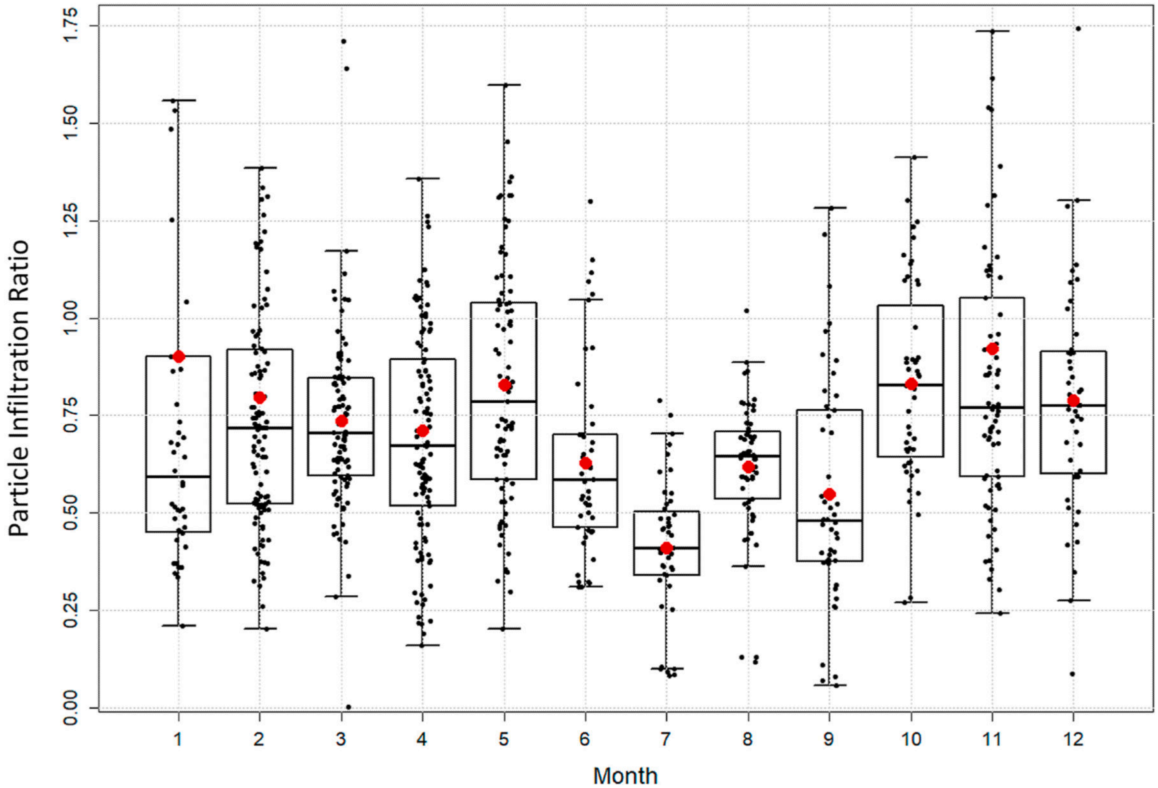

Figure 1.
Distribution of particle infiltration ratio by month in houses (N=810) in Atlanta

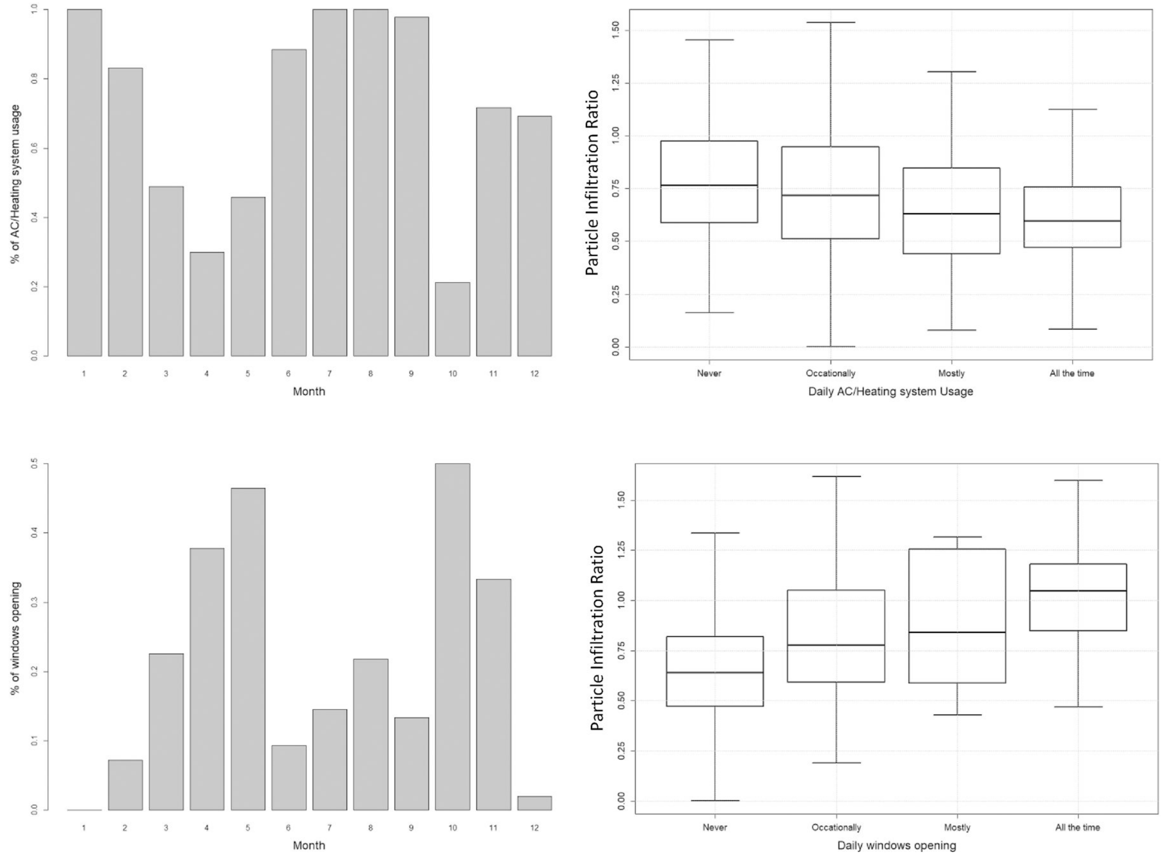

Figure 2. Distribution of particle infiltration ratio by HVAC/Heating system usage and windows opening in Atlanta.

(Top Left) Percentage of homes using HVAC/Heating system by month. (Top Right) Particle infiltration ratio by daily HVAC/Heating system usage. (Bottom Left) Percentage of household windows opening by month. (Bottom Right) Particle infiltration ratio by daily windows opening.

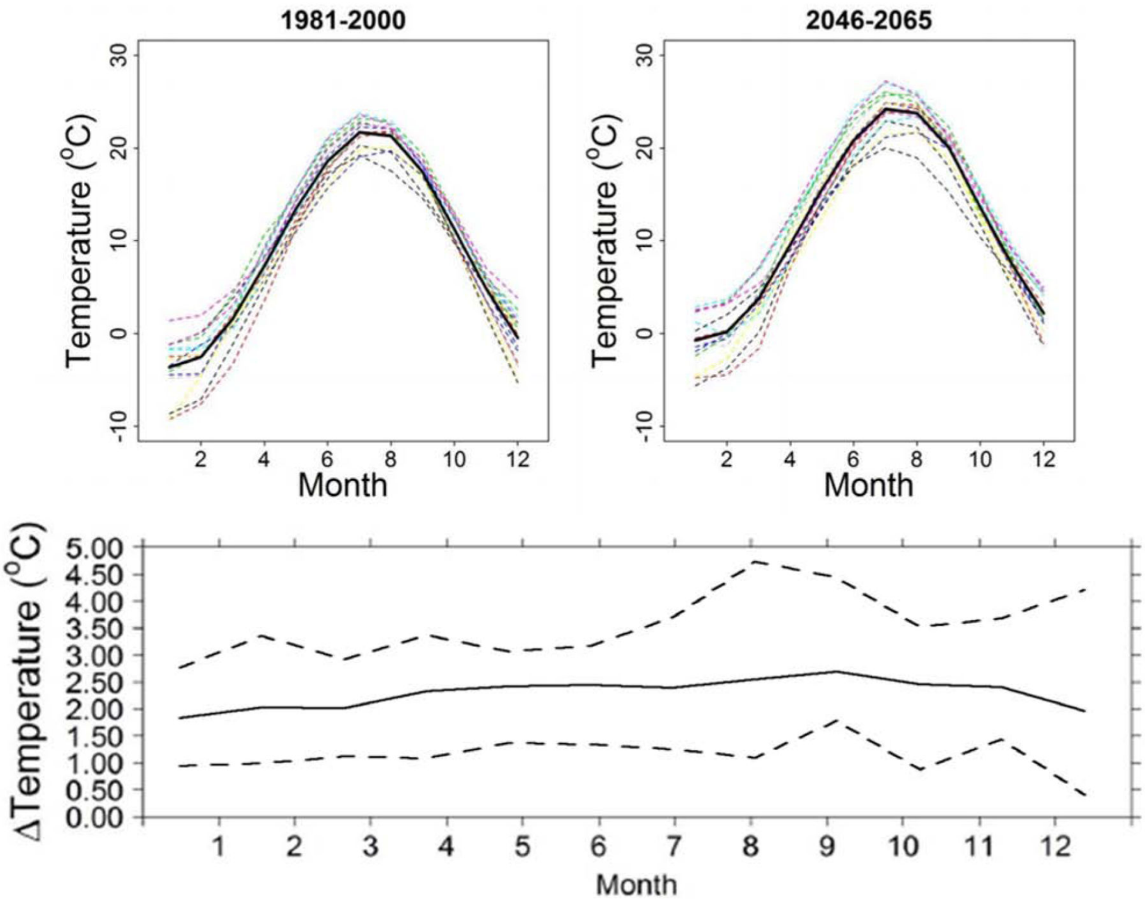

Figure 3. Projected mean monthly temperature for the past (1981–2000) and the future (2046–2065) time periods using 14 CMIP5 models (dashed lines) under the RCP4.5 intermediate scenario.

(Top Left and Top Right) The solid line is the ensemble 168 monthly mean outdoor temperature across the CMIP5 models. (Bottom) The solid lines are the overall monthly future-past temperature differences across the CMIP5 models while the dashed lines are ± 1 standard deviation from the overall mean. Mean monthly temperature projected to increase by 1.5–2.5°C in Atlanta, with larger increases in summer.

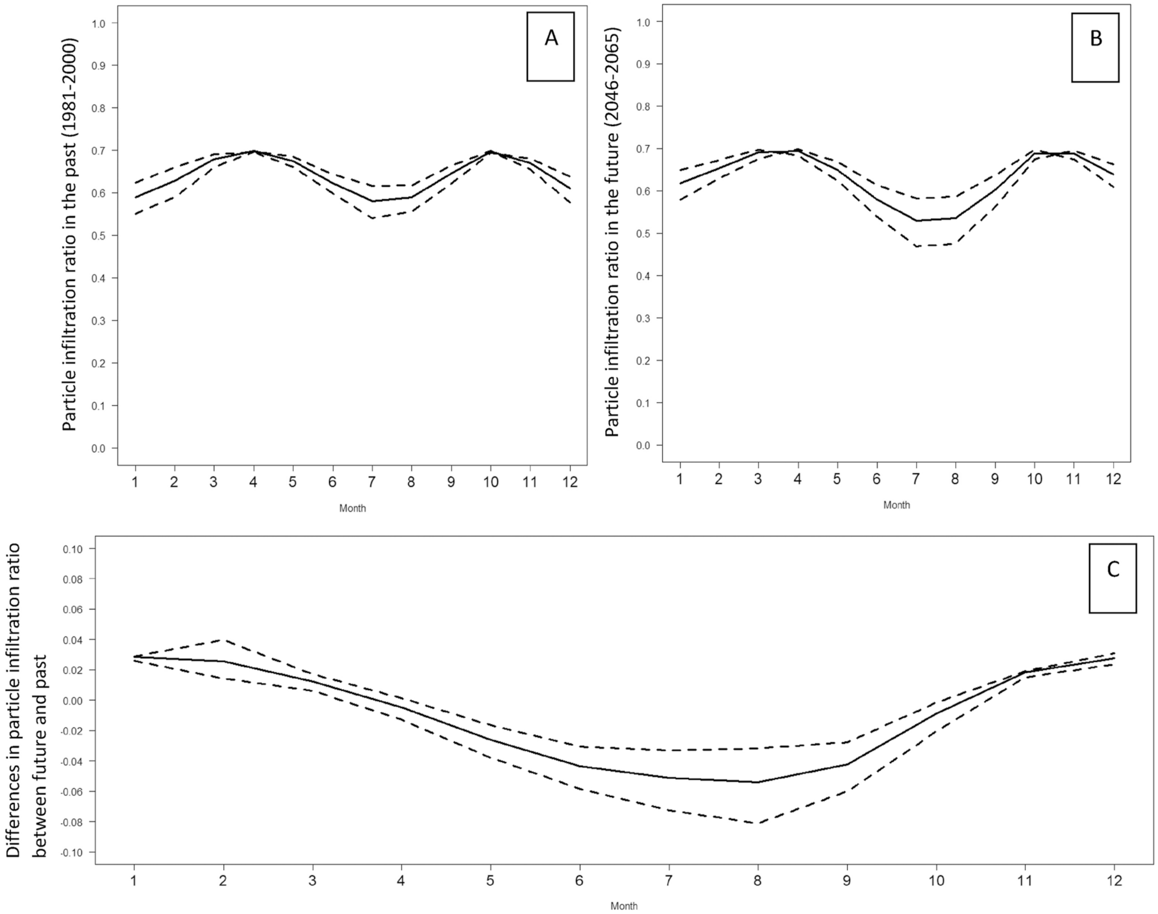

Figure 4. Projected mean monthly particle infiltration ratio for the past (1981–2000) and the future (2046–2065) time periods.

The solid lines show the overall monthly particle infiltration ratio in the past (Figure 4A), in the future (Figure 4B), or the differences in particle infiltration ratio between the two time periods (Figure 4C) using projected temperature from 14 CMIP5 models while the dashed lines indicate ± 1 SD from the overall mean.

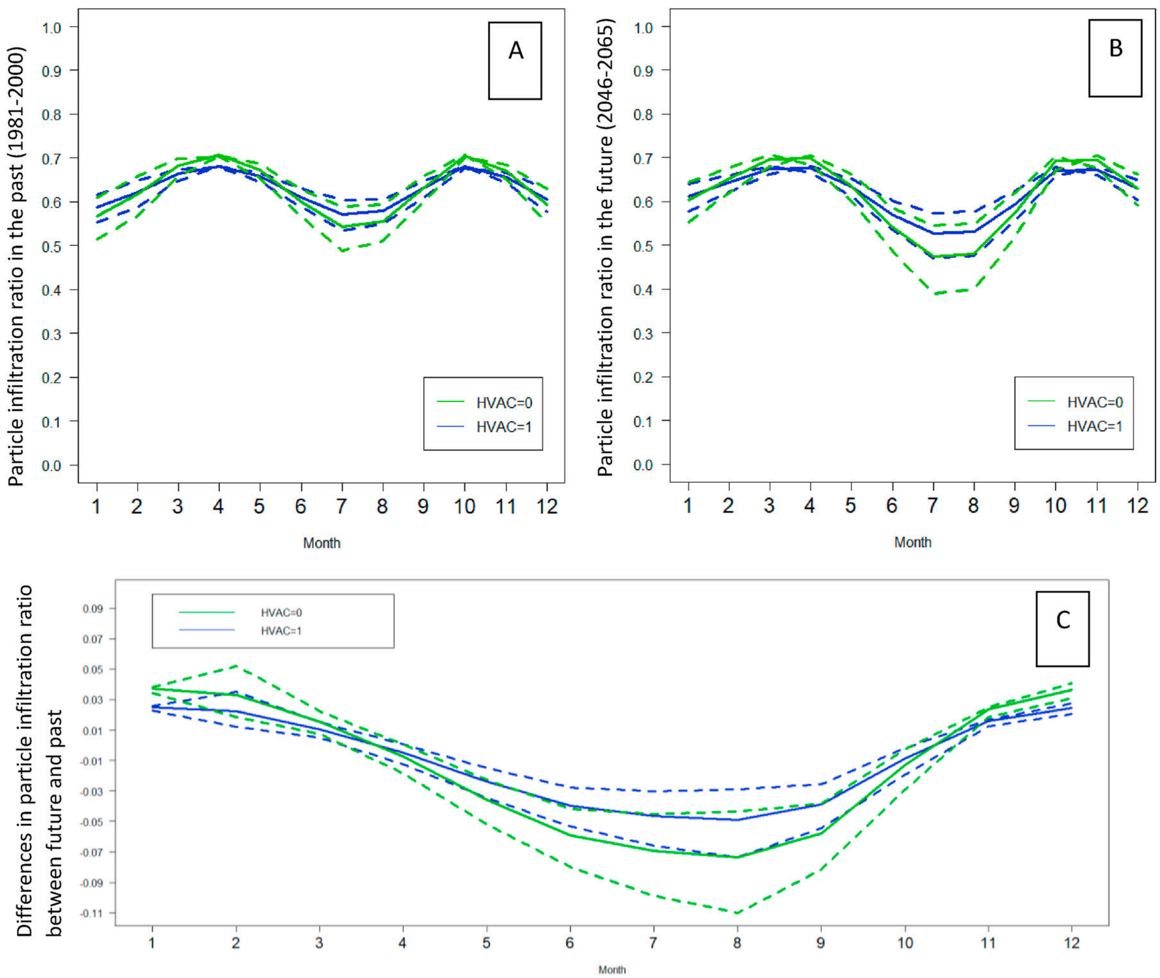

Figure 5. Projected mean monthly particle infiltration ratio for the past (1981–2000) and the future (2046–2065) time periods among homes with and without heating, ventilation, and air conditioning (HVAC) usage.

The solid lines show the overall monthly particle infiltration ratio in the past (Figure 5A), in the future (Figure 5B), or the differences in particle infiltration ratio between the two time periods (Figure 5C) using projected temperature from 14 CMIP5 models while the dashed lines show ± 1 SD from the overall mean. Green lines denote homes without HVAC and blue lines denote homes with HVAC usage

Table 1.

Summary of the sampling parameters, and meteorology parameters within the sampling duration.

	N (homes)	n (samples)	Mean ± SD	Median	Min	Max
Indoor $PM_{2.5}$ (μg/m^3)	60	810	10.2 ±15.8	6.8	0.11	289.0
Outdoor $PM_{2.5}$ (μg/m^3)*			10.9 ±4.7	10.3	3.2	60.5
Indoor sulfur (μg/m^3)	60	810	0.3 ± 0.2	0.2	0.02	1.1
Outdoor sulfur (μg/m^3)*			0.4 ±0.2	0.4	0.04	1.3
Indoor-outdoor particle infiltration ratio (i.e. sulfur ratio)						
All (HVAC=mixed)	60	810	0.74 ±0.39	0.68	0.00	3.64
HVAC=0	42	271	0.79 ±0.30	0.77	0.16	1.91
HVAC=1	58	539	0.72 ± 0.44	0.64	0.00	3.64
Meteorology^						
Ambient Temperature (°C)			18.4 ±7.5	18.3	−1.1	31.1
Indoor Temperature (°C)	60	769	22.2 ±2.4	22.1	14.5	28.0
Relative humidity (%)			62.3 ±13.8	62.0	0.0	97.0
Indoor Relative humidity (%)	60	769	51.2 ±9.4	51.2	18.6	75.1
Wind speed (m/s)			3.8 ±1.5	3.6	0.9	9.8
Precipitation (inch/day)			0.1 ±0.4	0.0	0.0	4.3

*Measurements of outdoor $PM_{2.5}$ and sulfur concentrations were conducted at the Jefferson Street center monitoring site

^Meteorology data for the homes in our study cohorts, including ambient temperature, relative humidity, wind speed, and precipitation, were obtained from the North American Regional Reanalysis (NARR) database. Indoor temperature and relative humidity were measured using HOBO Temperature/Relative Humidity 3.5% Data Logger.

Table 2.

Associations between meteorological or house physical factors and particle infiltration ratio in univariate mixed effect model

Variable	N	Coefficient estimate	Standard error	p-value
Meteorological Factors				
Outdoor Temperature (°C)	810	−0.009	0.001	<0.0001
Indoor Temperature (°C)	749	−0.022	0.006	<0.0001
Relative humidity (%)	810	−0.001	0.001	0.236
Indoor Relative humidity (%)	749	−0.004	0.002	0.011
Wind speed (m/s)	810	0.013	0.008	0.080
Precipitation (inch/day)	810	0.027	0.027	0.319
House Physical Factors				
House Age	810	0.0003	0.001	0.828
Square Footage (per 100 sq.ft)	810	−0.002	0.004	0.485
Number of Windows	810	0.126	0.071	0.149

Table 3.

Particle infiltration ratio -outdoor temperature exposure model parameters by different population scenarios (HVAC=mixed; HVAC=0; HVAC=1).

Dataset	Model	Coefficient estimate	Standard error	p-value
Full Dataset				
All Houses (N=810)	Intercept	0.622	0.066	<0.0001
	Temperature	0.032	0.007	<0.0001
	Temperatur^2	−0.001	0.0002	<0.0001
Houses without HVAC usage (N=255)	Intercept	0.518	0.247	0.0372
	Temperature	0.032	0.027	0.2408
	Temperatur^2	−0.001	0.001	0.2317
Houses with HVAC usage (N=523)	Intercept	0.691	0.073	<0.0001
	Temperature	0.024	0.008	0.0040
	Temperatur^2	−0.001	0.0002	<0.0001
Reduced Dataset *				
All Houses (N=649)	Intercept	0.480	0.036	<0.0001
	Temperature	0.029	0.004	<0.0001
	Temperatur^2	−0.001	0.0001	<0.0001
Houses without HVAC usage (N=189)	Intercept	0.422	0.174	0.0161
	Temperature	0.038	0.019	0.0467
	Temperatur^2	−0.001	0.0005	0.0162
Houses with HVAC usage (N=431)	Intercept	0.491	0.029	<0.0001
	Temperature	0.026	0.004	<0.0001
	Temperatur^2	−0.001	0.0001	<0.0001

* Reduced dataset excluded 138 sampling days with particle infiltration ratio greater than one. Furthermore, all exposure data from five households were excluded in the reduced dataset where over 70% of the measured particle infiltration ratio were greater than one in these households.