Identifying Housing and Meteorological Conditions Influencing Residential Air Exchange Rates in the DEARS and RIOPA Studies: Development of Distributions for Human Exposure Modeling

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Abstract

Appropriate prediction of residential air exchange rate (AER) is important for estimating human exposures in the residential microenvironment, as AER drives the infiltration of outdoor-generated air pollutants indoors. AER differences among homes may result from a number of factors, including housing characteristics and meteorological conditions. Residential AER data collected in the Detroit Exposure and Aerosol Research Study (DEARS) and the Relationships of Indoor, Outdoor and Personal Air (RIOPA) study were analyzed to determine whether the influence of a number of housing and meteorological conditions on AER were consistent across four cities in different regions of the US (Detroit MI, Elizabeth NJ, Houston TX, Los Angeles CA). Influential factors were identified and used as binning variables for deriving final AER distributions for use in exposure modeling. In addition, both between-home and within-home variance in AER in DEARS were quantified with the goal of identifying reasonable AER resampling frequencies for use in longitudinal exposure modeling efforts. The results of this analysis indicate that residential AERs depended on ambient temperature, the presence (or not) of central air conditioning, and the age of the home. Furthermore, between-home variability in AER accounted for the majority (67%) of the total variance in AER for Detroit homes indicating lower within-home variability. These findings are compared to other previously published AER distributions, and the implications for exposure modeling are discussed.

Disclaimer

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Introduction

Residential air exchange rate (AER), i.e., the number of whole house air exchanges with the outdoors per hour, is a significant contributing factor to the degree of infiltration of outdoor pollutants into indoor microenvironments. In addition, AER has a significant effect on the persistence of indoor-generated pollutants in the indoor air. Residential AER can be influenced by both housing conditions and meteorology, and those factors are used in attempts to model AER when direct measures might not exist (Chan et. al 2005, Breen et al. 2010). Infiltration via air leakage can be increased in homes with poor weatherproofing or poor or old construction, especially during cold weather when higher indoor-outdoor temperature gradients drive air flow. In addition, the presence and type of mechanical ventilation system in use in the home may affect AER (Thornburg et al. 2004). Finally, the use of open windows or doors for cooling purposes during warmer weather can increase natural ventilation, resulting in higher AERs (Wallace et al. 2006).

Appropriate population distributions for AER are required for modeling reasonable estimates of total population exposures to outdoor air pollutants, especially considering the large fraction of time people spend in residences. While some regionally-specific AER data are available (Murray and Burmaster), the critical factors that drive such regional differences are less clear. Identifying the crucial universal housing or weather factors that drive variances in AER can aid in understanding and quantifying geographic differences in AER distributions and provide a basis for selecting appropriate AER distributions for modeling exercises in absence of measured values. In addition, modeling studies also require as input AER sampling frequencies that capture the correct balance of within-home and between-home variance in AER. Adequately modeling this balance is required for reproducing appropriate variation in mean AER among individuals and estimating reasonable population distributions of indoor concentration and exposure (Wallace et al. 2006; Williams et al. 2003). Ideal AER sampling frequencies can be identified through analysis of longitudinal measurements of AER in the same house.

The present study examines measured AER data in four U.S. cities with the following specific objectives: 1) Quantify and generalize the influence of housing and meteorological conditions on residential AER 2) Develop AER distributions as a function of these influential factors for use in exposure modeling and 3) Provide recommendations for applying this distributions in longitudinal studies by quantifying within and between home variation in AER. With these goals in mind, AER data for Elizabeth, New Jersey; Houston, Texas; and Los Angeles, California were obtained from the Relationship among Indoor, Outdoor, and Personal Air (RIOPA) study, conducted in 1999-2001 to assess personal exposures to air toxics and particulate matter (Weisel et al. 2005a,b). AER data for Detroit were obtained from the Detroit Aerosol and Exposure Study (DEARS), a 2004-2007 study aimed at quantifying the relationship between central site pollutant concentrations and those in residential and personal locations (Williams et al. 2009).

The AER data from the DEARS and the RIOPA studies were assessed as a function of numerous home characteristics obtained from surveys of the exposure study participants. In addition, AER was examined as a function of several meteorological variables that were measured along with AER. These data were studied with the goal of identifying universal patterns in AER across cities as a function of factors that are easily quantified by available weather station or housing stock information. Final recommendations for AER distributions as a function of the most influential factors are presented, and compared with previously published AER distributions for different regions and seasons. These recommendations can guide the selection of appropriate AER distributions for modeling studies in cities for which no measured AER data are available. Finally, longitudinal AER data from the DEARS study were examined with the goal of quantifying the balance between in-home and between-home variances in AER, and recommended AER sampling rates are presented.

Methods

AER Measurements

The DEARS AER measurements were obtained in Wayne Co. Michigan homes in 2004-2007 on a maximum of five consecutive days in one or both of two seasons: summer (July-August) or winter (January-March). Detailed descriptions of the repeated measures study design, analytical measurement protocols, and subject populations involved have been reported (Phillips et al. 2011; Williams et al. 2009).

Measurements were taken in 105 houses in summer, 90 houses in winter, and 67 houses in both seasonsEach measurement represented a 24 hr monitoring period (9am to 9am ± 2.5 hr) with measurements taking place from Tuesday morning through Sunday morning. The daily measurements were made using the perfluorocarbon tracer method first reported by Dietz and Cote (1982) and Dietz et al. (1986) and Brookhaven National Laboratory (BNL) provided guidance on the number of sources to be used in each home relative to its floor structure. Field blanks and collocated duplicates (each 5% of the total population) were used to assess quality assurance features of the data collections during each monitoring season. The method detection AER limit by season was determined to be well below 0.1 hr^{-1} (typically on the order of 0.042 hr^{-1}). Precision error averaged well under 10% during the DEARS. Raw data was used without the need for any blank correction or transformation to calculate the average daily air exchange rate for each DEARS residence by season and household.

The RIOPA AER measurements were obtained in 300 residences from 1999-2001; approximately 100 homes were tested in each RIOPA city (Elizabeth, NJ; Houston, TX; and Los Angeles, CA.). The measurements were 48-hour AER averages obtained using a perfluorocarbon tracer method. These methods have been described in detail elsewhere (Weisel et al. 2005b). Measurements were made in all 4 seasons, but only two seasons in each house.

Housing Characteristics

The housing characteristics as provided by participants in each study are described in this section. Sample sizes for these variables are provided in the Results section.

Housing Age. In DEARS, home age in years was provided as a continuous variable. The mean home age was 63.9 ± 23.8 years with a range of 6.0 to 125. In RIOPA, the year of construction was provided. The categories were 1995 or after, 1985-1994, 1975-1984, 1960-1974,1945-1959, 1900-1944, and before 1900. This home age variable was missing from 68 RIOPA homes. These date categories were translated to five age categories, and each house was assigned an age based on the date of the study. These categories were <=15 years, 16-40 years, 41-100 years, and 100+ years. Again for consistency, the continuous DEARS ages were also binned into these categories.

Housing Type. Housing type information was available in both the DEARS and the RIOPA studies. The DEARS categories were mobile home, attached single family (e.g, duplex) and apartment, and detached single family. The vast majority of all residences (> 85%) being the latter. All structures had to have independent air handling systems, entrances, and exhaust features.

The RIOPA categories were mobile home, single family, townhouse attached on 1 side, townhouse attached on 2 sides, other, and six categories of apartments based on the number of units: 2, 3-4, 5-9, 10-19, 20-49, and 50+ units. There were no significant differences in overall mean AER among the apartment categories or between the types of townhouses (using the Kruskal-Wallis test at the 5% level), so a single apartment and a single townhouse category were used to be consistent with the DEARS groups.

Heating Source. In the DEARS, the heating source categories were electric, radiator, gas, oil, wood fireplace, or other (e.g. kerosene). The majority of the DEARS homes (80 % ± SD) used forced air gas furnaces which were often in operation from October through April due to the extended heating season for this location. In RIOPA, the heating information was limited to whether the home had a forced-air central heating system (yes/no).

Air Conditioning. Air conditioning (AC) data were available in both studies. The AC types were central unit, window unit, both central and window unit, and none. In the DEARS, due to the average age of the homes and milder ambient temperatures, natural ventilation (open doors/windows) was used by 35% of the participants in lieu of any type of mechanical air conditioning. In RIOPA, there were some inconsistencies in the variable indicating home AC unit type and that indicating daily AC use, mainly in Houston. For example, there were many houses having daily use of a central AC system indicated, but the house itself was categorized as having no AC. When this type of conflict occurred, the daily value was assumed to be correct.

Measurement Period-specific Settings. In addition to the above universal housing properties, information specific to each 24- or 48-hour measurement period was also provided. In both the DEARS and the RIOPA, these settings were available: window/door status (open/closed), heating system in use (yes/no), and AC in use (yes/no). In the DEARS, fan use (yes/no) was also obtained. This included recovery of this type of information as both ordinal (y/n) as well as discrete (length of time the event occurred). In the present analysis we only present analyses associated with the ordinal DEARS response.

Meteorology

Figure 1 is a map of the U.S. showing the mean number of annual heating degree days (HDD) in each state, based on data from the National Climatic Data Center (2010) for the years 1970-2009. The HDD values are a measure of climate; they represent the annual sum of the difference between 65°F and the average daily temperature (when it is below 65°F.) Such regional differences in climate can drive differences in patterns of behavior (for example, air conditioner (AC) use) as well as differences in air leakage due to temperature gradients. The four cities studied are located in states having relatively different HDD values, and thus represent a broad range of the U.S. climate. Determining the similarities and differences in AER among these cities can aid in selecting appropriate AER probability distributions for future exposure modeling studies in other locations.

Several meteorological variables were available in both studies. In DEARS, daily ambient air temperatures, humidity values and wind speeds were provided. Daily (24-hr) meteorological data, matched to the daily collection periods of each home, were obtained from a local State of Michigan ambient air monitoring site (Allen Park, MI) which was centrally-located with respect to the DEARS study neighborhoods (Williams et al. 2009).Average temperatures were then calculated for each house for each 5-day study period. Five-day averages for humidity and wind speed were not calculated as the interpretation of the effect of such averages on AER would be unclear. In RIOPA, average temperature, wind speed, and humidity were provided for each 48-hour measurement period.

Analysis Methods

AER was examined as a function of the housing and weather conditions described above. The continuous variables in the dataset (for example, the meteorological variables and house age) were examined to identify reasonable breakpoints for binning into categories. Multiple sets of category definitions were examined during the exploratory analysis, but only the final categories are presented here. In general, the final categories were those that produced the most significant differences between groups.

Differences in AER between groups were assessed with the Wilcoxon signed rank test (for 2 groups) or the Kruskal-Wallis test (for more than 2 groups). These tests were performed in SAS version 9.1 (SAS, Inc., Cary, NC) using the NPAR1WAY procedure. Final lognormal distributions for AER for each city were fit to the data using maximum likelihood estimation, via the SAS UNIVARIATE procedure.

Variance in AER

The variance patterns of the AER measurements for DEARS were assessed using the intra-class correlation coefficient (ICC). As defined here, the ICC quantifies the balance between within-home and between-home variance:

$$ICC = \frac{\sigma_b^2}{\sigma^2} = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_w^2} \quad (1)$$

where σ_b^2 is the between-home variance, and is calculated as:

$$\sigma_b^2 = N^{-1} \sum_{j=1}^{N} (AER_{j,mean} - \overline{AER})^2 \quad (2)$$

where N is the number of homes, $AER_{j,mean}$ is the mean AER for home j, and $\overline{AER}$ is the overall mean AER. The within-home variance σ_w^2 is

$$\sigma_w^2 = (NM)^{-1} \sum_{j=1}^{N} \sum_{k=1}^{M} (AER_{jk} - AER_{j,mean})^2 \quad (3)$$

where M is the number of days, $AER_{j,k}$ is the AER for home j on day k.

The ICC was calculated for both DEARS seasons and for the entire study period.

Comparison of Derived AER Distributions with Existing Empirical Distributions

The final AER distributions derived from the DEARS and RIOPA studies were compared with other sources of residential AER distributions available for use in exposure modeling. Empirical AER distributions for different regions of the US by season have previously been developed (Murray and Burmaster, 1995). These distributions were based on data collected from 2844 households in different US states using a perflourocarbon tracer technique. The distributions were estimated for each season in 4 US regions defined by the number of annual heating degree days (HDD) similar to Figure 1 but with only four categories: Region 1: HDD ≥ 7000; Region 2: 5500 ≤ HDD <7000; Region 3: 2500 ≤ HDD <5500; and Region 4: HDD < 2500.

More recently, a methodology for estimating AER distributions from distributions of air leakage measurements from U.S. homes has been reported (Chan et al., 2005) for conventional and low-income houses in the U.S and for all U.S. homes. In addition, an equation for estimating AER based on NL was given:

$$AER = 48\left(\frac{2.5}{H}\right)^{0.3}\frac{NL}{HF} \tag{4}$$

where H is ceiling height and F is a scaling factor, and reported a best fit value of 16 for F when their distributions were fit to national AER data. Using an estimate of ceiling height of 8 ft (2.43 m) and F=16, we calculated AER distributions from the reported NL data for comparison with AER data from the DEARS and RIOPA.

Results and Discussion

Influence of Meteorology and Housing Factors on AER: Identifying Important Factors

AER as a function of meteorology and housing conditions is detailed below, with significant tabular results presented in Tables 1 and 2.. Box plots for all comparisons are given in the Appendix. Unless otherwise noted, the AER values that are being compared are as follows: In Detroit, the reported AER values used in these analyses are the mean of the 5 24-hour AER rates measured in each season in each house. In Elizabeth, Houston, and Los Angeles, the value is the mean 48-hour AER measurement. These factors were assessed to identify final categories for binning AER and fitting probability distributions.

Season and Temperature

Seasons were defined as: spring -- March, April, and May; summer -- June, July, and August; fall -- September, October, and November; winter -- December, January, and February. However, in DEARS, a few "winter" measurements were taken in March. The seasonal results for the RIOPA cities have been previously reported (Yamamoto et al. 2009).

As shown in Table 1, there was a marked increase in AER in summer versus winter for Detroit (1.92 vs. 1.11 hr,$^{-1}$ $p=0.03$). In Houston, there was an overall seasonal effect ($p<0.01$). Summer versus winter was the only statistically significant difference, but in this city AER in summer was lower (0.52 vs. 0.74 hr^{-1}). In Los Angeles, there was also an overall effect of season ($p<0.01$); summer versus winter was again the only significant difference (1.52 vs. 0.75 hr^{-1}). There was no overall affect of season in Elizabeth. This appeared to be due to the similarity of AER magnitude in homes during the winter with those in homes without AC in the summer in this city.

Since the AER patterns with season were not uniform across locations, temperature was also explicitly considered as a categorical variable for examining AER. It was sensible to consider temperature as opposed to season, since season as defined strictly by month will contain different numbers of cooling/heating days in different climatic regions and people respond directly to temperature in terms of opening windows or turning on heating or cooling systems. Yamamoto et al. (2009) examined AER as a function of heating, neutral, and cooling seasons based on the indoor/outdoor temperature differential of the houses. Wallace et al (2006) did likewise and even examined additional temperature variables as possible AER factors. The present study examined the absolute ambient outdoor temperature to determine reasonable temperature categories. For exposure modeling purposes, AER distributions based on outdoor temperature may be more useful because distributions of indoor temperatures for cities may be poorly characterized, but outdoor temperature data are readily available.

Different temperature breakpoints were considered, but a value 65°F - 68°F provided the best separation of AER values, especially when other variables (such as AC use) were considered. This breakpoint value may have been due to the clustering of temperatures in these two studies, as many of the homes were studied in winter and summer; however, an examination of the measurement period settings for each house indicated that in these studies, an average daily temperature of around 65°F corresponded to a large uptick in the number of homes turning on their AC unit. Therefore, the AER measurements were split into two categories, those occurring in cold weather (<=65°F) or warm weather (>65°F). The term "weather" is used here as a convenience; the average temperature used for binning the values was that for the measurement period (the 48-hour average for RIOPA and 5-day average for DEARS). AER differences with temperature were not enlightening when considered alone; however, when temperature was considered with other variables (e.g. air conditioning status) it proved important as a factor, as described in subsequent sections.

Wind Speed and Humidity

Average daily wind speed (or the 48-hour average, for the RIOPA cities) was binned into 3 ranges: 0-5, 5-10, and >10 mph; there were no single observations of wind speed (WS) greater than 15 mph in any city. There was no evidence of effect of wind speed overall or within season in the Detroit area or Elizabeth. WS did appear to influence AER in Houston and Los Angeles. There was lower AER at WS <= 5 mph in these cities when compared to higher speeds However, WS also was examined on days when the windows were open. For these days, there was no effect on AER any city in any season. Therefore, it may be that the impacts of WS in Houston and LA are just indicative of other variables occurring simultaneously with wind speed (such as window use during warm windy weather in these cities). Humidity was binned into 4 ranges, 0-50%, 50-75%, 75-90%, and >90%. There was no evidence of any significant effect of humidity on AER in any city in any season. Therefore, neither WS nor humidity was considered as influential factors for binning AER.

Housing Age

AER was examined as a function of housing age for all locations to determine this factor should be used for binning AER when developing probability distributions. In most locations, the age of the home significantly impacted AER in colder weather (average temperature <=65°F), but not in warmer weather. In colder weather (when a positive indoor temperature and pressure gradient exist), older homes have increased AER. In Detroit, this effect was only apparent when the newest homes (<= 15 years of age) where compared with all other homes (Table 1; 0.70 vs. 1.23 hr^{-1}); using this same age breakpoint in the other 3 cities also resulted in higher AER in older homes for Houston (0.33 vs. 0.76 hr^{-1}) and Los Angeles (0.65 vs. 1.00 hr^{-1}). The difference in Elizabeth was not statistically significant. Therefore, for the purpose of developing AER distributions for exposure modeling, the current AER data were stratified into older versus newer homes at a breakpoint of 15 years of age when deciding on final probability distributions for AER.

Housing Type

Housing type was also examined for all locations as a potential influential binning variable, both overall and within a given temperature category. A significant overall effect of type in warm weather was evident in Houston (p=0.02) and Los Angeles (p=0.02). In Los Angeles, single family homes had higher AER than apartments (1.77 vs. 1.04 hr^{-1}), while in Houston, the main difference was that mobile homes had elevated AER (Table 2). Differences in cold weather were evident for attached versus detached single family homes in Detroit (1.63 vs. 1.14 hr^{-1}), and for single family homes versus apartments in Elizabeth and Los Angeles (1.55 vs. 1.04 and 1.09 vs. 0.69 hr^{-1}). Because universal conclusions could not be made about the effects of housing type across cities and temperatures, this variable was not considered as a potential grouping variable for determining final AER distributions for exposure simulations. While it is clear that mobile homes and apartments probably have different AER from single family detached homes, more data are necessary before well-founded generalizations with respect to housing type may be made. In addition, these differences are likely confounded by differences in AC status in these homes. Currently, differences in AER due to housing types should be considered to be represented by the overall variability in AER across the city and AC status. Thus, caution should be used when simulating a population having a distribution of housing types markedly different from that used to develop the distributions.

Air Conditioning and Heating

The influence of air conditioning (AC) type and heating source on AER was examined in all cities in warmer and cold weather, to identify any critical influence of these housing characteristics AC had a large impact on AER rates in warm weather (>65 F) only, as expected.

In all cities, homes with central AC had significantly lower AER than homes with no AC and homes with window AC (Table 2). The differences between homes with no AC and homes with window AC were not as clear. In the Detroit area and in Houston, AER rates in homes with no AC were significantly higher than homes with window AC, but in Elizabeth and Los Angeles there were no significant differences. Thus, the final categories for consideration for exposure modeling were selected as homes with central AC and homes with no central unit.

Air conditioning use during individual warm-weather measurement periods was also examined for homes that had AC, and window use was examined for all homes. These variables were examined to confirm the driving forces between the differences in AER in homes with and without AC. In all locations, AER was significantly higher during the measurement periods when the AC unit was off. Window use also significantly increased AER in all cities during warm weather, and the highest AER in Detroit was seen when windows were open and a fan was used. In addition, windows were open in 74% of the measurement periods in homes without AC in warm weather (273 of 371 periods). It can thus be concluded that the higher air exchange rates in summer in homes with no central AC are due to increases in natural ventilation for cooling purposes.

There was no effect of heating source in the Detroit area in either season. This was likely due to the fact that the Detroit-area homes were very homogeneous in heating method (80% of the homes used gas heat). In Elizabeth, Houston, and Los Angeles there was no effect of heating type in winter. There was an effect in summer (homes with central heat had higher AER), but this is likely attributable simply to the strong correlation between having central air and having central heat. Thus, heating source was not a strong indicator of AER during the winter in these homes.

Based on these results, AC status (but not heating source) was identified as a binning variable for developing final recommended AER distributions.

Development of AER Distributions for Exposure Modeling

As the results above indicate, AER patterns within season were city-specific, and it was difficult to make generalizations regarding season with respect to AER. However, it does appear from this analysis that window use, AC prevalence, and AC use are at least partly (and perhaps mostly) responsible for temperature and seasonal differences, with these differences being greatest in homes that use windows for cooling purposes. In addition, it may be that regional differences in AER are also due to regional differences in these factors. For example, window use may vary across regions at the same temperature due to differences in the prevalence of AC. It was also clear that house age had an effect when temperatures were colder, likely through increased leakage in older homes when a positive indoor-outdoor temperature gradient drives air flow.

House age (in cold weather), and AC status (in warm weather) were identified above as influential binning variables for developing AER distributions. When these factors are considered together with temperature, the differences in regional patterns are decreased. Figure 2 illustrates well the fairly universal pattern of AER across cities when AER is stratified by these factors. When homes are tightly closed (such as in cold weather and when central AC is present) AER is low. AER is increased in older homes in cold weather due to leakage driven by indoor-outdoor temperature gradient, but is highest in warm weather when no AC is present and airflow is increased due to window use. The two temperature bins used here appear to be adequate to capture differences in AER in these studies. Other studies where more data are available (especially at moderate temperatures), could perhaps better characterize patterns of AER during periods when temperatures are intermediate between hot and cold.

Final means, standard deviations, and percentiles for AER for these groups are given in Table 2. The data were also fit to probability distributions; in all cases the data fit a lognormal shape best, as is typical with AER data. The final geometric means and geometric standard deviations of these best-fit distributions are also given in the table. When the data were categorized into these groups, there were no significant differences in AER among Detroit, Elizabeth, and Los Angeles within each group. This has significance to exposure modeling, because it suggests that data for any relatively temperate city may be appropriate for any other, as long as these factors are considered. However, the AER for Houston was significantly lower than each of the other cities in at least 3 of the four groups. The reason for this is unclear, but it is possible that warm-weather AER in Houston is decreased compared to the other, more temperate cities because the humidity levels there result in tighter control of open doors and windows, while smaller indoor-outdoor temperature differentials in colder weather decrease air leakage, and thus AER. This suggests that data from more hot, humid locations is somewhat unique when compared to other U.S. climates.

Limitations

The influential factors identified herein as consistent with the theoretical understanding of AER (e.g. air flow is given by temperature gradients in winter especially in "leakier" older homes), and the resulting binned distributions can aid in predicting AER appropriately under different conditions. However, several of these distributions were generated from a small number of homes (N=8 in three cases) and the corresponding uncertainty in these distributions should be recognized.

Any remaining differences in AER distributions among the studied cities could be due to variables that were incompletely examined herein. It did appear that there are differences among different housing types, but these differences were difficult to generalize due to the small sample sizes, and thus stratifying these AER data further would be of limited use in developing AER distributions for modeling. In any event, it is clear that differences due to these factors appear to be smaller in magnitude than those due to AC, window use, and house age. If more finely defined distributions are required for a given modeling application, physical/mechanistic AER models of homes that take into account more specific information about housing properties in a given city could be used to revise or augment these more general AER distributions (e.g. Breen et al. 2010).

Comparison with Other Residential AER Distributions

Using the Murray and Burmaster (M-B, 1995) heating degree day (HDD) bins, Detroit and Elizabeth fall into Region 2, while Los Angeles is Region 3 and Houston Region 4. The final DEARS and RIOPA AER distributions (i.e. those given in Table 3) are plotted against the M-B data corresponding M-B Regions in Figure 3. The cold weather distributions for older and newer homes are compared plotted against M-B fall and winter distributions (left-hand panels), while the warm weather distributions for homes having Central AC and No AC are plotted against M-B spring and summer distributions (right-hand panels). Note that Murray and Burmaster do not report a summer distribution for Region 2 due to lack of data.

In general, the distributions for Detroit, Elizabeth, and LA with both cold and warm weather were somewhat higher than the corresponding M-B distributions. In particular, older homes and homes with no central AC had significantly elevated AER relative to the M-B distributions, indicating the importance of considering housing stock when selecting AER distributions for a specific geographical area. An exception was the lower AER at the 95th percentile in Elizabeth for newer homes in cold weather and homes with AC in warm weather, although these two distributions were based on a limited sample size (N=8 in both cases). In Houston, these housing-driven characteristics were also evident, as homes with central AC and newer homes had lower AER than the M-B percentiles for Region 4.

The comparison of the final AER distributions with those estimated from the leakage distributions of Chan et al. (2005) are shown in Figure 4. In all four cities, the estimated Chan

"All US" distribution fell within the range spanned by the four final AER distributions derived in this paper. With the exception of Houston, the estimated Chan "Low Income" distributions more closely approximated the AER distributions in older homes and homes with no central AC than did the "Conventional" distributions.

In both comparisons of the measured AER distributions from exposure studies with available estimates of AER distributions for US homes, significant differences were evident. Use of M-B derived AER distributions would underestimate AERs for all four cities in the winter, most significantly for Detroit and Elizabeth. Similarly, use of the M-B summer AER distributions would also underestimate AERs for these two cities, but would also overestimate AERs for Houston. Although seasonal comparisons were not possible with the Chan et al. (2005) distributions, the distinction between AERs for conventional and low-income homes for the U.S. provided a better fit to the measurements analyzed here. Estimation of AER distributions for these cities using the Chan et al. (2005) equation and NL distributions would generally produce lower over- or under-predictions compared to the M-B distributions. While the total number of AER measurements for the DEARS and RIOPA studies is far smaller than used to derive the distributions in Murray and Burmaster (1995) and Chan et al. (2005), these discrepancies, which are almost certainly based on housing stock differences, could be important for exposure modeling applications. Both housing age and AC prevalence information can be obtained on relatively fine spatial scales for many metropolitan areas from U.S. Census data (United States Census Bureau 2011), and such information should be considered when selecting AER distributions for specific geographic locations.

Variance Characteristics of AER in DEARS

In the DEARS study, five consecutive AER measurements were collected for each home in two seasons, allowing for the analysis of variance both within and between homes. The intra-class correlation coefficients (ICCs) for AER in Detroit are given in Table 3. The overall ICC was 0. 67 indicating that the majority (67%) of the overall variance in AER was due to differences between homes. Within a season, the ICC was even higher (ICC=0.73 in winter and ICC=0.81 in summer). These results indicate that in general, the between-home variance accounts for the largest fraction of the total variance in AER. Thus AER was relatively stable over time in each home, especially within a season, when compared to differences between homes. The high ICC within season indicates that a single 24- or 48-hour measurement within a season may be relatively representative of the mean seasonal AER for that home.

The ICC can provide guidance when selecting a sampling scheme for AER in exposure modeling. Reproduction of target ICC (and thus an appropriate balance of variances) can be achieved through selection of AER resampling rate. As an example, consider the four final categories for which AER distributions were calculated for Detroit. Each home in a simulation of the city would be assigned a cold weather distribution (based on house age) and a warm weather distribution (based on central AC). However, without considering the longitudinal patterns of AER it may be unclear how many samples from these distributions should be selected for each home for a year-long simulation. Based on the ICCs calculated from DEARS, a reasonable recommendation is to select a single value from each distribution for each house, to be assigned to each day according to the average temperature. When this method was applied to a typical house by sampling from the AER distributions above based on ambient daily temperature at the Detroit for the entirety of 2004 (Wayne County Airport weather station), the resulting overall AER ICC value was 0.58 (1.0 in winter and 0.62 in summer). For 2005, the values were 0.55 (1.0 in winter and 0.92 in summer). These values are reasonably close to the calculated ICC values for this study.

Conclusions

Understanding the universal factors that influence AER in different regions of the country can aid in the development or selection of appropriate AER distributions for use in human exposure modeling. When little or no AER are available, both the housing stock and climate of the city to be studied should be considered. The current analysis of AER data from studies in the Detroit area, Elizabeth, NJ, Houston, and Los Angeles suggests that when temperature, central AC prevalence, and home age are considered, much of the regional variation in AER rates is diminished. Furthermore, between-home variability in AER dominates within-home variability. These findings have the potential to increase the amount of appropriate AER data available for use in exposure simulations in cities or regions where no data have been collected and to assist modelers in formulating the relative importance of between-home and within-home variability of AER. Significant differences were found in comparisons of DEARS and RIOPA AER distributions with other available estimates of AER distributions for U.S. homes, indicating that the influential factors identified in this analysis (temperature, central AC prevalence, and home age, which are consistent with the theoretical understanding of AER) may provide more appropriate characterization of AER variability for exposure simulations in U.S. cities. These distributions may be particularly useful in EPA stochastic human exposure models for air pollutants that use mass-balance algorithms for estimating indoor-outdoor pollutant concentration relationships and pollutant concentrations in residential microenvironments.

References

Breen, M., Breen, M., Williams, R., Schultz, B. Predicting residential air exchange rates from questionnaires and meteorology: model evaluation in central North Carolina. *Environmental Science and Technology* 2010:44: 9349-9356.

Burke, J.M., Zufall, M.J., and Ozkaynak, H. A population exposure model for particulate matter: Case study results for PM2.5 in Philadelphia, PA., *J Expos Anal Environ Epidem* 11, 470, 2001.

Chan W, Nazaroff W, Price P, Sohn M, and Gadgil A. Analyzing a database of residential air leakage in the United States. *Atmospheric Environment* 2005: 39:3445–3455.

Dietz R., and Cote E. Air infiltration measurements in a home using a convenient perfluorocarbon tracer technique. *Environ Int* 1982: 8: 419–433.

Dietz R., Goodrich R., Cote E., and Wieser R. Detailed description and performance of a passive perfluorocarbon tracer system for building ventilation and air exchange measurements, measured air leakage of buildings. In: Trechsel H.R., and Lagus P.L. (Eds.). *ASTM STP 904*. American Society for Testing and Materials: Philadelphia, PA, 1986 pp. 203–264.

Georgopoulos, P., Wang, S., Vyas, V., Sun, Q., Burke, J., Vedantham, R., McCurdy, T., Özkaynak, H. A source-to-dose assessment of population exposures to fine PM and ozone in Philadelphia, PA, during a summer 1999 episode. *J Expos Anal Environ Epid* 2005: 15: 439-457.

Isakov, V., Touma, J., Burke, J., Lobdell, D., Palma, T., Rosenbaum, A., Özkaynak, H. Combining regional- and local-scale models for use in environmental health studies. *Journal of the Air & Waste Management Association*, 2009: 59: 461-472.

Kinney PL, Chillrud SN, Ramstrom S, Ross J, Spengler JD. Exposures to multiple air toxics in New York City. *Environ Health Perspect*. 2002: Suppl 4:539-46.

Meng QY, Turpin BJ, Polidori A, Lee JH, Weisel C, Morandi M, Colome S, Stock T, Winer A, Zhang J. PM2.5 of ambient origin: estimates and exposure errors relevant to PM epidemiology: Supplemental Material. *Environ Sci Technol*. 2005: 39(14):5105-12.

Murray D.M. and Burmaster D.E. Residential air exchange rates in the United States: Empirical and estimated parametric distributions by season and climatic region. *Risk Analysis* 1995: 15(4):459-465.

National Climatic Data Center. www.ncdc.noaa.gov. 2010.

Özkaynak, H., Frey, H.C., Burke, J., Pinder, R. Analysis of coupled model uncertainties in source-to-dose modeling of human exposures to ambient air pollution: A PM2.5 case study. *Atmospheric Environment*, 2009: 43: 1641-1649.

Pandian, M.D., Ott, W.R. and Behar, J.V. Residential air exchange rates for use in indoor air exposure modeling studies, *J. Expo. Anal. Environ. Epidemiol.*, 1993: 3:407–416.

Phillips, M., Rodes, C., Thornburg, J., Shamo, F., Whitmore, R., Chowdhury, D., Allpress, J., Vette, A., Williams, R. Optimizing recruitment and retention strategies for the Detroit Exposure and Aerosol Research Study (DEARS). RTI Press.doi:10.3768/rtipress.2010.2010.mr0021.1011.

Thornburg J., Rodes, C., Lawless, P., Stevens, C., and Williams, R. A pilot study of the influence of residential HAC duty cycle on indoor air quality. *Atmospheric Environment* 2004: 38: 1567-1577.

United States Census Bureau (2011). American Housing Survey. Data available at http://www.census.gov/housing/ahs/data/.

US EPA. (2008a). Total Risk Integrated Methodology (TRIM) Air Pollutants Exposure Model Documentation (TRIM.Expo/APEX, Version 4.3). Volume 1: Users Guide. Report no. EPA-452/B-08-001a. Office of Air Quality Planning and Standards, Research Triangle Park, NC. Available at: http://www.epa.gov/ttn/fera/human_apex.html

US EPA. (2008b). Total Risk Integrated Methodology (TRIM) Air Pollutants Exposure Model Documentation (TRIM.Expo/APEX, Version 4.3). Volume 2: Technical Support Document. Report no. EPA-452/B-08-001b. Office of Air Quality Planning and Standards, Research Triangle Park, NC. Available at: http://www.epa.gov/ttn/fera/human_apex.html.

US EPA 2012. The Detroit Exposure and Aerosol Research Study (DEARS). www.epa.gov/dears.

Wallace, W., Williams, R., Suggs, J., Jones, P. Estimating Contributions of Outdoor Fine Particles to Indoor Concentrations and Personal Exposures: Effects of Household Characteristics and Personal Activities. ORD Report (APM 214).EPA/600/R-023. March 2006. Washington, DC.

Williams, R., Suggs, J., Rea, A., Sheldon, L., Rodes, C., Thornburg, J. The Research Triangle Park particulate matter panel study: modeling ambient source contribution to personal and residential PM mass concentrations. *Atmospheric Environment*, 2003:37: 5365-5378.

Williams R., Rea A., Vette A., Croghan C., Whitaker D., Wilson H., Stevens C., McDow S., Burke J., Fortmann R., Sheldon L., Thornburg J., Phillips M., Lawless P., Rodes, C., Daughtrey H. The design and field implementation of the Detroit Exposure and Aerosol Research Study (DEARS). , *J. Expo. Anal. Environ. Epidemiol*. 2009:19:643–659.

Williams, R., Jones, P., Carry Croghan, Thornburg, J., Rodes, C. The influence of human and environmental exposure factors upon personal NO_2 exposure. *J. Expo. Anal. Environ. Epidemiol*.. 2011: Doi:10.1038/jes.2011.20.

Weisel C. P., Zhang,J., Turpin B. J., Morandi M. T., Colome S., Stock T. H., Spektor D.M., Korn L., Winer A., Alimokhtari S., Kwon J., Mohan K., Harrington R., Maberti S., Shendell D., Giovennetti R., Lee J. H. (2005a) The relationships of indoor, outdoor and personal air (RIOPA) study: study design, methods and quality assurance/control results. *J. Exposure Anal. Environ Epidemiol.*, 2005a:15: 123-137.

Weisel, C.P., Zhang, J., Turpin, B.J., Morandi, M.T., Colome, S., Stock, T.H., Spektor, D.M., Korn, L., Winer, A.M., Kwon, J., Meng, Q.Y., Zhang, L., Harrington, R., Liu, W., Reff, A., Lee, J.H., Alimokhtari, S., Mohan, K., Shendell, D., Jones, J., Farrar, L., Maberti, S. and Fan, T.

Relationships of Indoor, Outdoor, and Personal Air (RIOPA). Part I. Collection methods and descriptive analyses, *Res. Rep. Health Eff. Inst.*, 2005b:130:1–107.

Yamamoto N, Shendell D, Winer A., and Zhang J. Residential air exchange rates in three major US metropolitan areas: results from the Relationship Among Indoor, Outdoor, and Personal Air Study 1999–2001. *Indoor Air* 2010: 20: 85–90.

Table 1. Seasonal differences in AER in four locations.

	Detroit (DEARS)			Elizabeth (RIOPA)			Houston (RIOPA)			Los Angeles (RIOPA)		
	N	**AER (hr^{-1}) Mean (SD)**	**p value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**p value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**p value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**p value(s)**
Season												
Winter	90	1.11 (0.67)	p=0.03	35	1.41 (1.14)	NS	39	0.74 (0.49)	p< 0.01[1]	34	0.75 (0.51)	p< 0.01[1]
Spring	NA			31	1.13 (1.01)		33	0.73 (0.91)		31	1.17 (0.72)	
Summer	105	1.92 (1.91)		45	1.26 (1.00)		47	0.52 (0.53)		58	1.52 (1.11)	
Fall	NA			52	1.05 (0.78)		45	0.68 (0.61)		59	1.00 (0.83)	

[1]Summer versus Winter

Table 2. Housing factors significantly impacting AER in at least one location in either colder (<=65 F) or warmer (>65 F) measurement periods. Significant two-way comparisons for each city are noted. An N value of "-" indicates a category not present in city.

	Detroit (DEARS)			**Elizabeth (RIOPA)**			**Houston (RIOPA)**			**Los Angeles (RIOPA)**		
	N	**AER (hr^{-1}) Mean (SD)**	**p value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**p value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**P value(s)**	**N**	**AER (hr^{-1}) Mean (SD)**	**p value(s)**
Housing Age at <=65 F												
Newer homes (<= 15 yrs)	10	0.70 (0.36)	p=0.03	8	0.66 (0.23)	NS	8	0.33 (0.21)	0.02	28	0.65 (0.73)	p<0.01
Older homes (>15 yrs)	86	1.23 (0.79)		63	1.15 (1.03)		32	0.76 (0.58)		57	1.00 (0.58)	
Housing Type at >65 F												
Single family homes	-			12	0.84 (0.50)	NS	76	0.47 (0.35)	<0.01[1]	38	1.77 (1.24)	p<0.01[2]
Apartments	-			32	1.56 (1.09)		4	0.37 (0.25)		40	1.04 (0.72)	
Mobile homes	2	2.31 (2.99)	NS	0			31	1.05 (1.03)		2	2.25 (0.34)	
Single family attached	5	1.54 (1.11)		-			-			-		
Single family detached	86	1.94 (2.03)		-			-			-		
Housing Type at <=65 F												
Single family homes	-			31	1.55 (1.35)	p=0.04	40	0.70 (0.47)	NS	42	1.09 (0.62)	p<0.01[2]
Apartments	-			68	1.04 (0.78)		0			40	0.69 (0.65)	
Mobile homes	0			0			6	0.58 (0.93)		3	0.87 (0.13)	
Single family attached	10	1.63 (0.81)	p=0.04	-			-			-		
Single family detached	81	1.14 (0.77)		-			-			-		
AC at >65 F												
Central AC	17	0.87 (1.27)	p< 0.01[3] p< 0.01[4]	6	0.50 (0.32)	p<0.01[3] p=0.03[4]	72	0.45 (0.27)	p< 0.01[3] p< 0.01[4]	43	1.01 (0.77)	p= 0.03[3] p< 0.01[4]
Window AC	57	1.98 (2.05)	p=0.03[4]	32	1.35 (0.96)		35	0.83 (0.87)	p< 0.01 [4]	11	2.01 (1.39)	
No AC	19	2.89 (1.84)		3	2.19 (1.32)		6	2.03 (0.68)		27	1.80 (1.07)	

[1]vs. Mobile homes
[2] vs. Apartments
[3]vs. Window AC
[4]vs. No AC

Table 2. AER (hr^{-1}) by Final Category: Detroit, Elizabeth, Houston, and Los Angeles.

	N	Mean	Std	P5	P25	P50	P75	P95	GM	GSD
Detroit (DEARS)										
Cold, Newer Homes	10	0.702	0.365	0.378	0.52	0.623	0.744	1.644	0.64	1.54
Cold, Older Homes	86	1.232	0.794	0.364	0.591	1.022	1.586	2.943	1.01	1.91
Warm, Central AC	21	0.899	1.236	0.155	0.25	0.311	0.573	3.566	0.47	2.89
Warm, No Central AC	76	2.212	2.024	0.42	0.843	1.823	2.881	6.102	1.57	2.37
Elizabeth (RIOPA)										
Cold, Newer Homes	8	0.656	0.233	0.393	0.486	0.559	0.868	1.032	0.62	1.41
Cold, Older Homes	63	1.152	1.031	0.323	0.507	0.758	1.382	4.14	0.85	2.14
Warm, Central AC	8	0.626	0.361	0.109	0.275	0.721	0.936	1.036	0.50	2.26
Warm, No Central AC	43	1.419	1.008	0.303	0.645	1.037	2.154	3.399	1.09	2.14
Houston (RIOPA)										
Cold, Newer Homes	8	0.328	0.213	0.092	0.142	0.283	0.495	0.689	0.27	2.06
Cold, Older Homes	32	0.76	0.582	0.182	0.276	0.66	1.006	2.288	0.58	2.19
Warm, Central AC	69	0.436	0.259	0.125	0.256	0.381	0.53	1.103	0.37	1.79
Warm, No Central AC	46	0.956	0.909	0.229	0.356	0.561	1.153	2.744	0.68	2.22
Los Angeles (RIOPA)										
Cold, Newer Homes	28	0.647	0.728	0.169	0.294	0.423	0.794	1.321	0.47	2.08
Cold, Older Homes	57	1.003	0.578	0.316	0.584	0.801	1.399	2.244	0.86	1.76
Warm, Central AC	31	0.89	0.672	0.26	0.449	0.71	0.979	2.704	0.71	1.95
Warm, No Central AC	50	1.732	1.124	0.212	0.978	1.445	2.401	4.353	1.38	2.11

Figure 1. Average annual heating degree days by state 1970-2009. Data from the National Climatic Data Center (NCDC 2010).

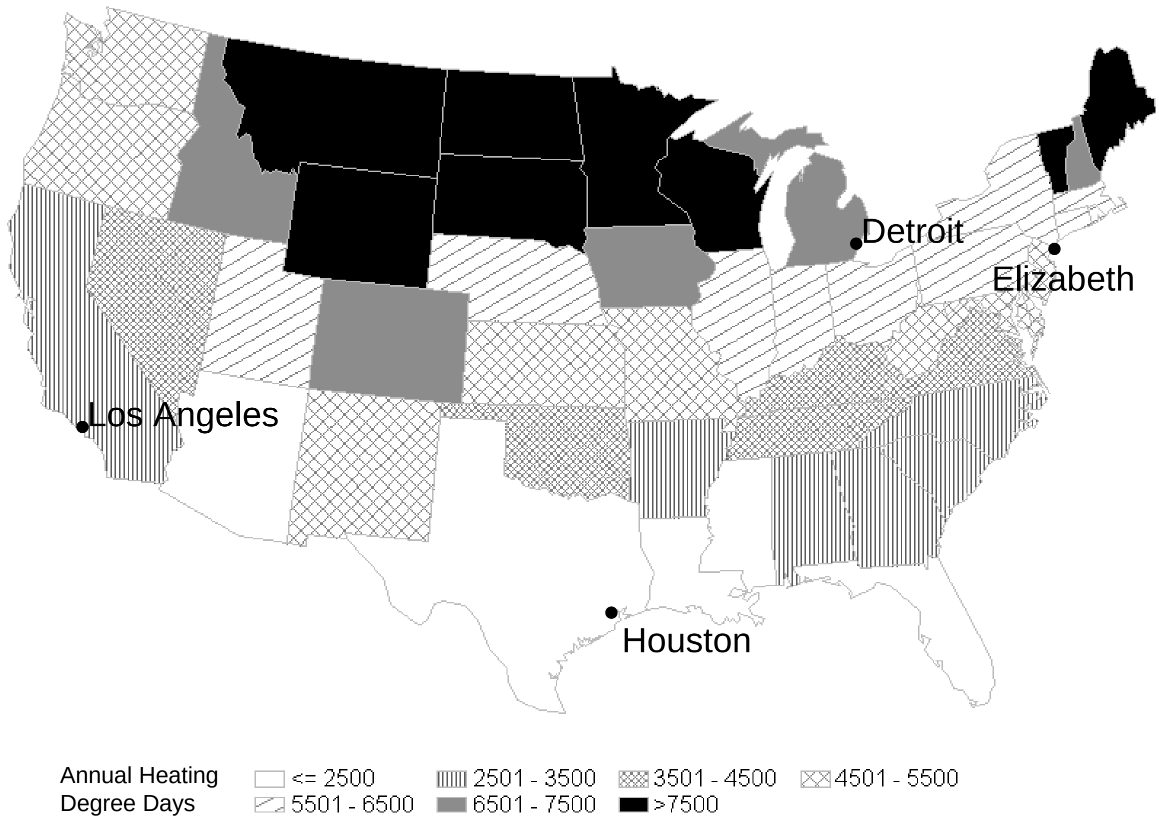
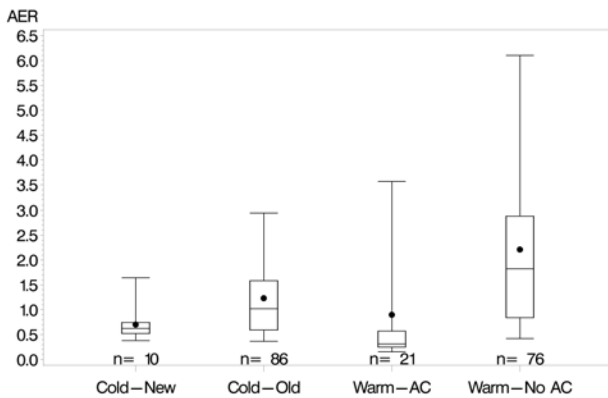
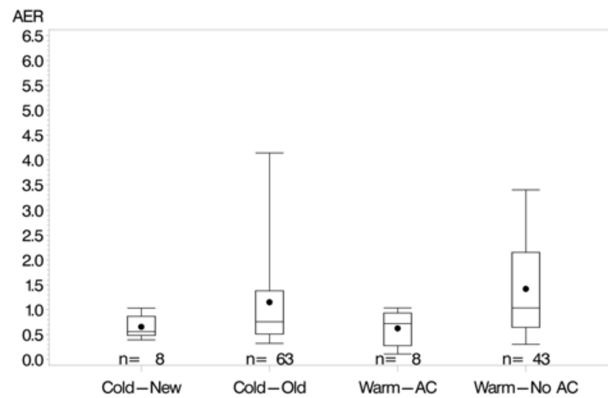


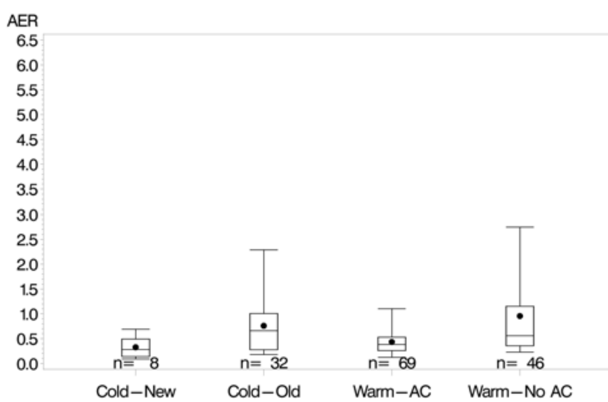
Figure 2. AER(h^{-1}) as a function of final categories for exposure modeling: temperature, home age, and central AC status.



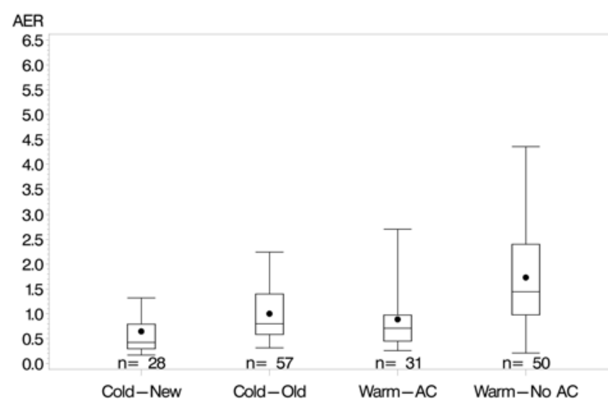
Detroit (DEARS)



Elizabeth (RIOPA)



Houston (RIOPA)



Los Angeles (RIOPA)

Figure 3. Comparison of the final AER distributions for four cities with those of Murray and Burmaster (M-B, 1995) for the corresponding region and seasons (left, Cold weather distributions compared with the M-B Winter and Fall; right, Warm weather distributions compared with M-B Spring and Summer). A: Detroit (DEARS) and Elizabeth (RIOPA) compared M-B Region 2; B: LA (RIOPA) compared with M-B Region 3, and C: Houston (RIOPA) compared with M-B Region 3.

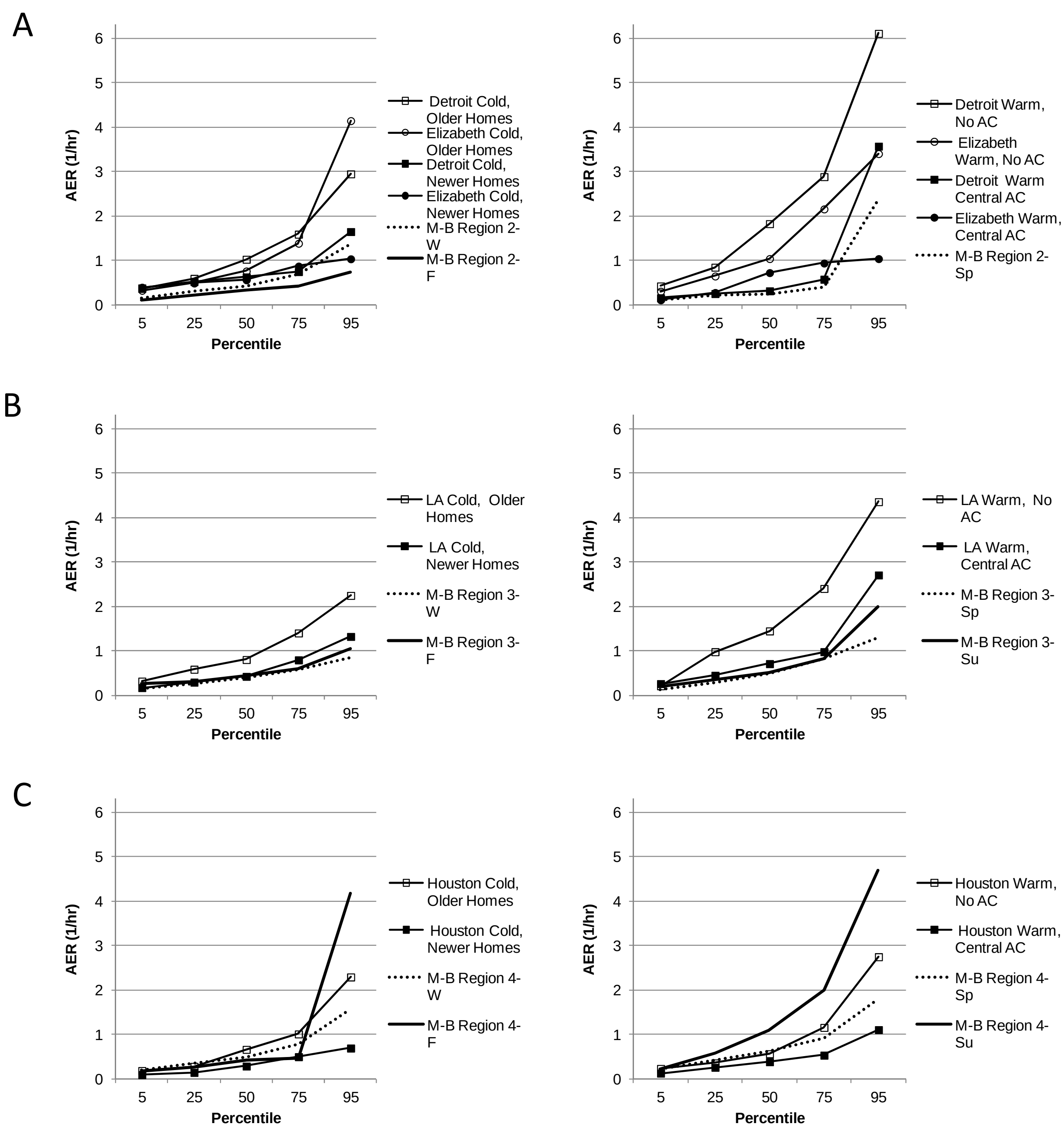
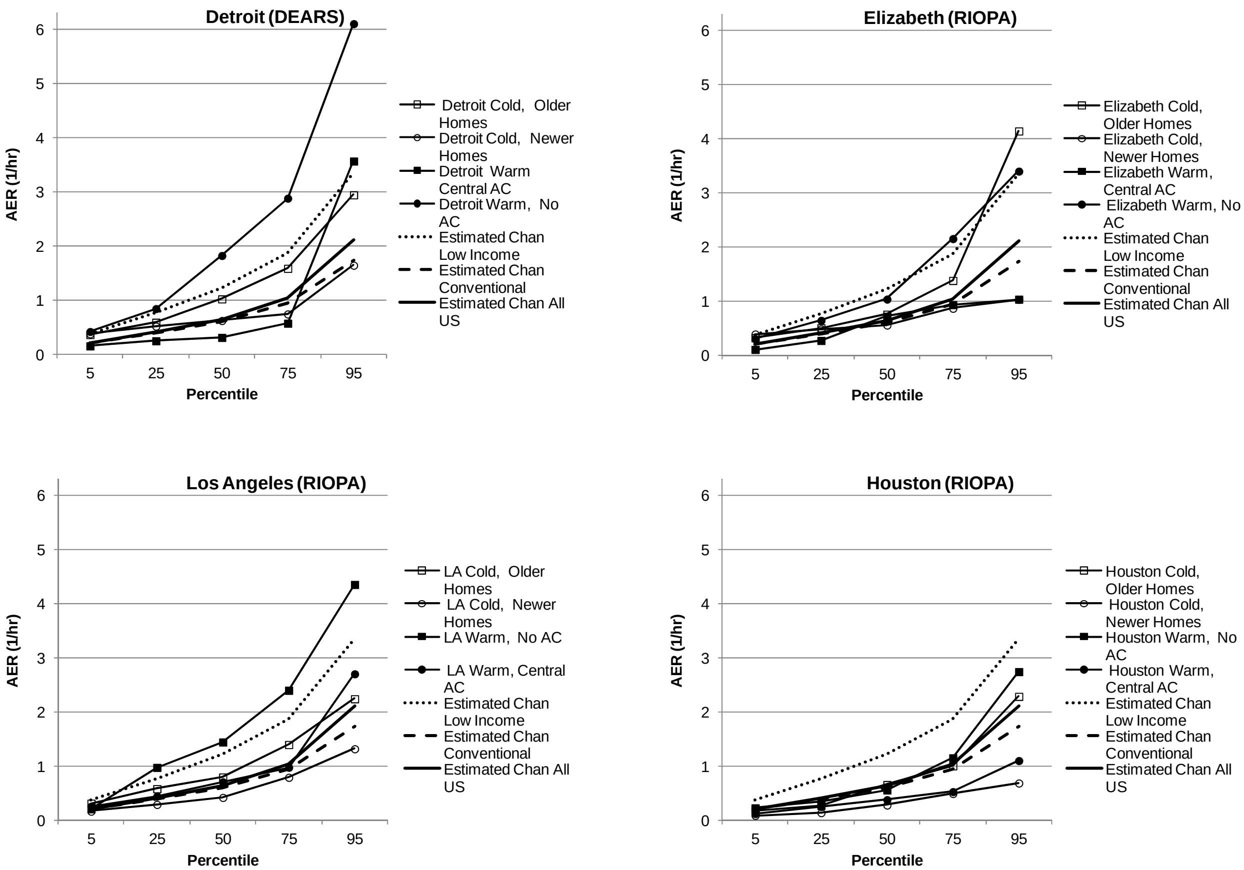


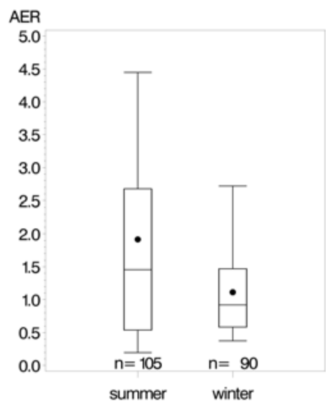
Figure 4. Comparison of the final DEARS and RIOPA AER distributions with those estimated from Chan et al (2005).



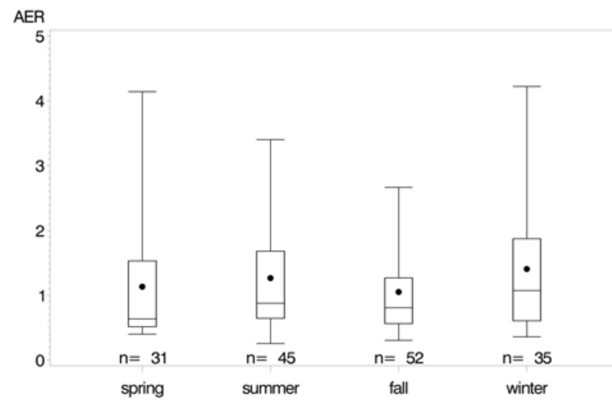
Appendix

Box plots comparing data distributions for various factors by city (medians are represented by the midline of the boxes, the means by the black dots, and the first and third quartiles by the ends of the boxes; whiskers extend to the 5th and 95th percentiles).

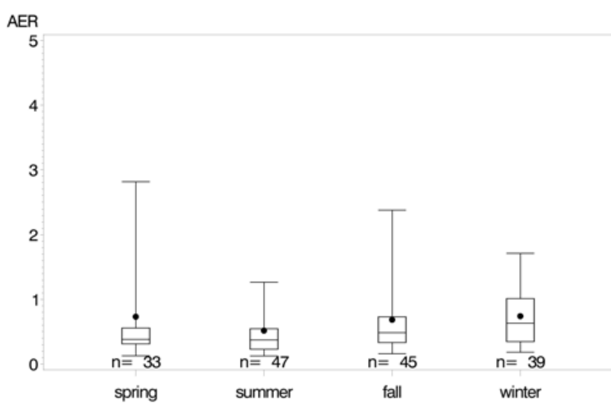
Figure A1. AER (h^{-1}) by season: spring (March-May), summer (June-August), fall (September-November), and winter (December-February).



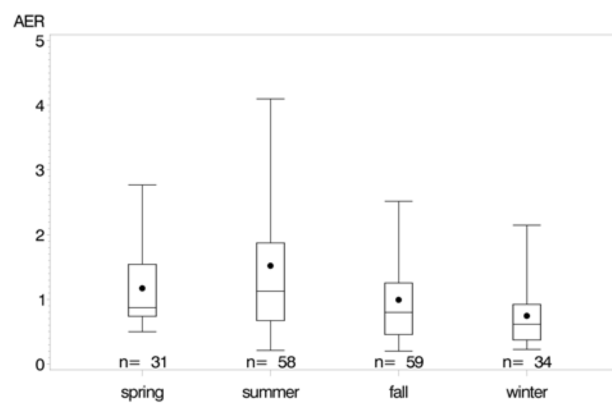
Detroit (DEARS)



Elizabeth (RIOPA)

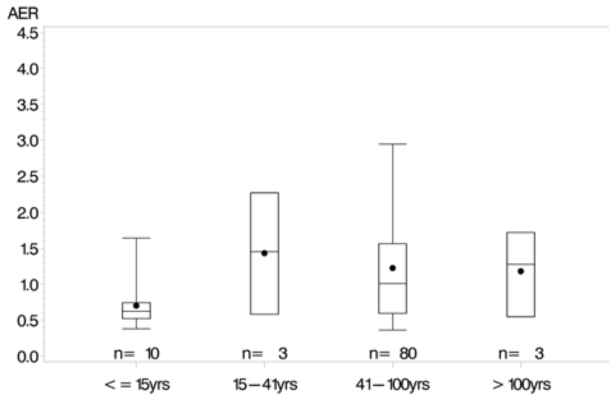


Houston (RIOPA)

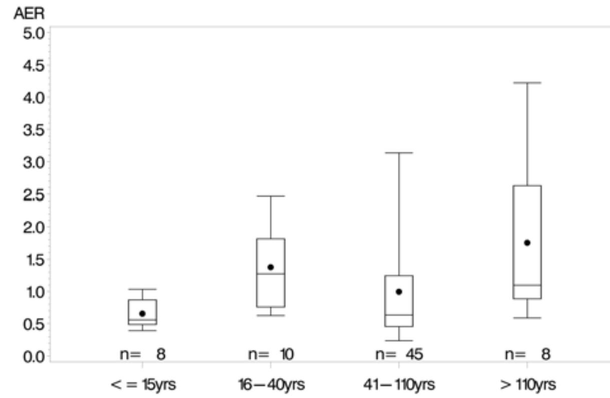


Los Angeles (RIOPA)

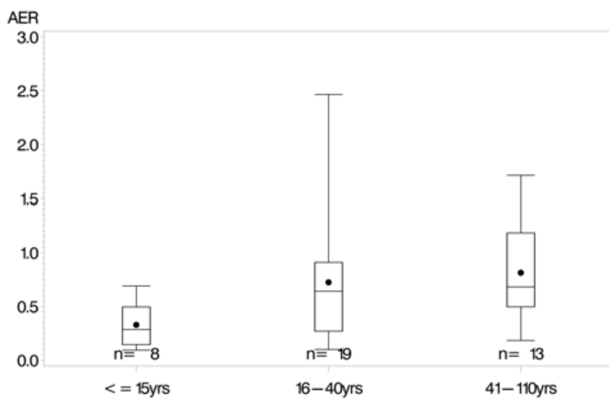
Figure A2. AER(h^{-1}) by house age in colder weather (T<65 degrees F).



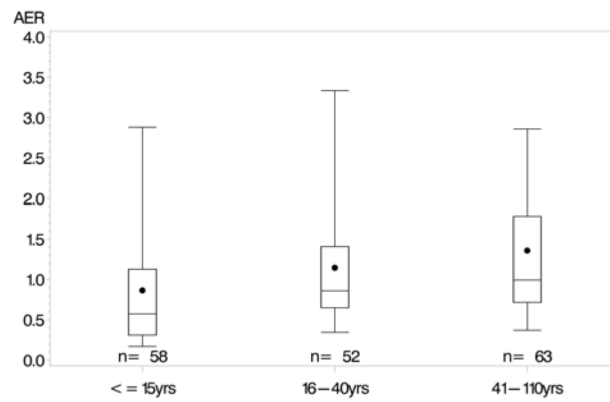
Detroit (DEARS)



Elizabeth (RIOPA)

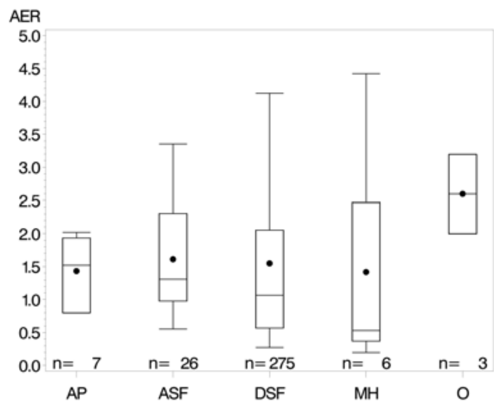


Houston (RIOPA)

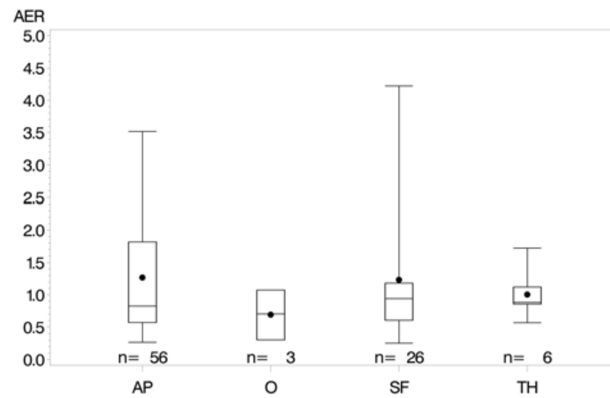


Los Angeles (RIOPA)

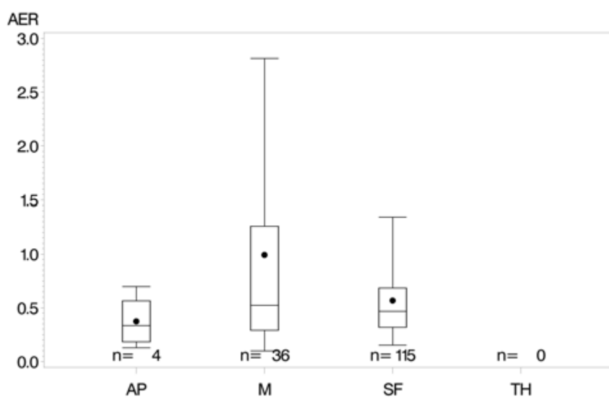
Figure A3. AER(h^{-1}) by housing type. In DEARS: apartment (AP), attached single family (ASF), detached single family (DSF), mobile home (MH), and other (O). In the other cities: apartment (AP), mobile home (M), other (O), single family (SF) and townhouse (TH).



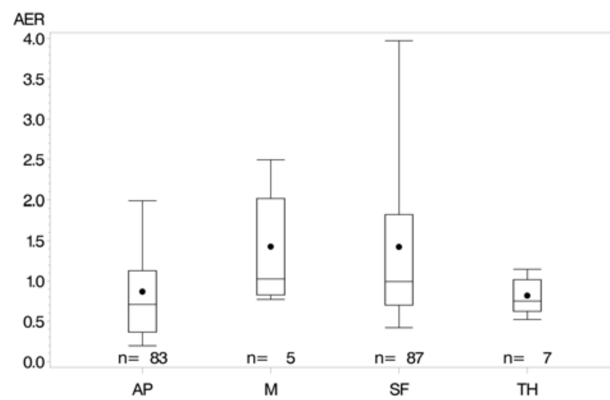
Detroit (DEARS)



Elizabeth (RIOPA)

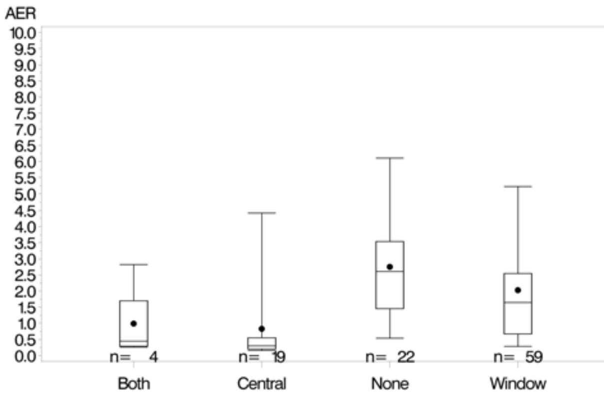


Houston (RIOPA)

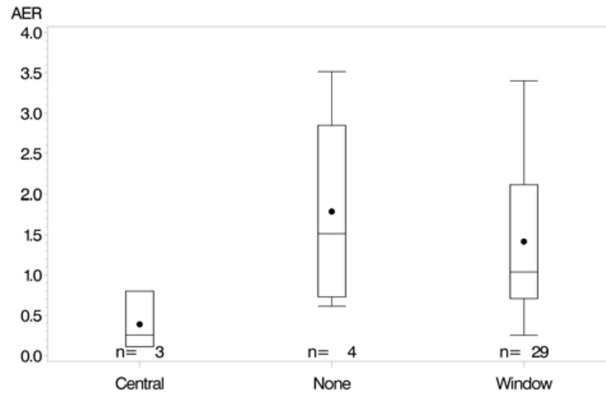


Los Angeles (RIOPA)

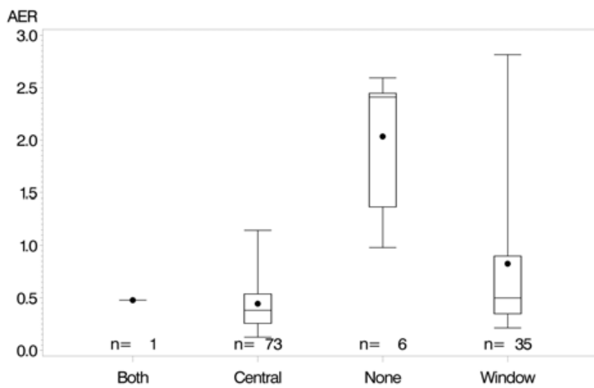
Figure A4. AER(h^{-1}) by AC type, warm days. "Both" indicates both central and window units.



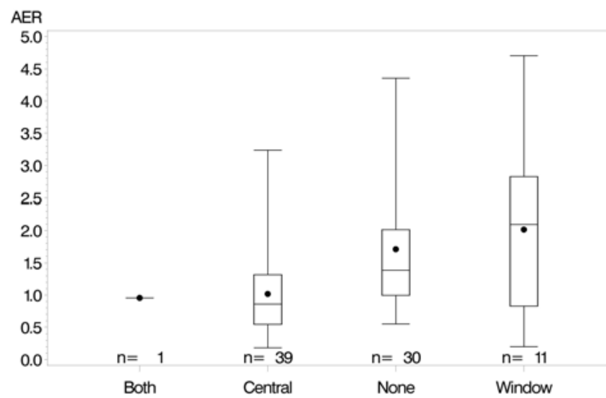
Detroit (DEARS)



Elizabeth (RIOPA)

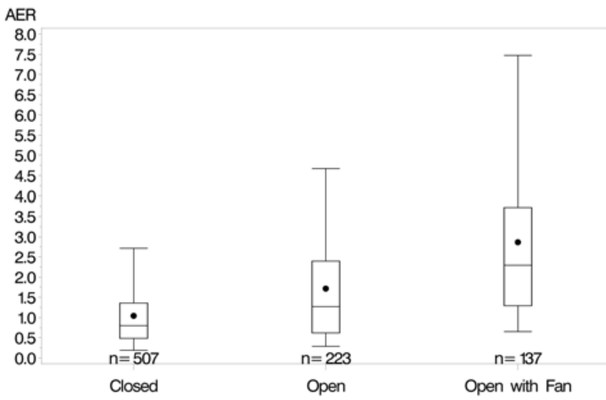


Houston (RIOPA)

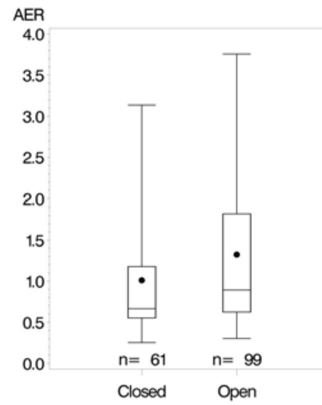


Los Angeles (RIOPA)

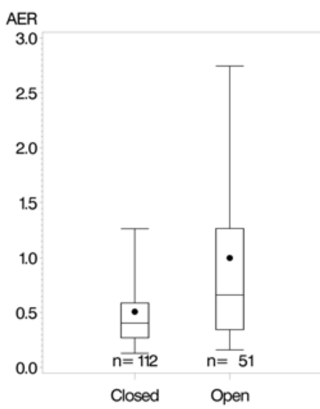
Figure A5. AER(h^{-1}) by window status for individual measurement periods (DEARS, 24-hour period, other cities 48-hour period).



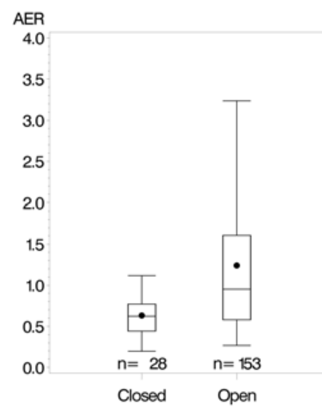
Detroit (DEARS)



Elizabeth (RIOPA)



Houston (RIOPA)



Los Angeles (RIOPA)