Published in final edited form as:
Indoor Air. 2014 February ; 24(1): 103–112. doi:10.1111/ina.12052.

The relationship between indoor and outdoor temperature, apparent temperature, relative humidity, and absolute humidity

Jennifer L. Nguyen, ScD[1], **Joel Schwartz, PhD**[1,2], and **Douglas W. Dockery, ScD**[1,2]

[1] Department of Environmental Health Harvard School of Public Health 401 Park Drive Boston, MA 02215

[2] Department of Epidemiology Harvard School of Public Health 677 Huntington Avenue Boston, MA 02215

Abstract

Introduction—Many studies report an association between outdoor ambient weather and health. Outdoor conditions may be a poor indicator of personal exposure because people spend most of their time indoors. Few studies have examined how indoor conditions relate to outdoor ambient weather.

Methods and Results—The average indoor temperature, apparent temperature, relative humidity (RH), and absolute humidity (AH) measured in 16 homes in Greater Boston, Massachusetts, from May 2011 - April 2012 was compared to measurements taken at Boston Logan airport. The relationship between indoor and outdoor temperatures is non-linear. At warmer outdoor temperatures, there is a strong correlation between indoor and outdoor temperature (Pearson correlation coefficient, $r = 0.91$, slope, $\beta = 0.41$), but at cooler temperatures, the association is weak ($r = 0.40$, $\beta = 0.04$). Results were similar for outdoor apparent temperature. The relationships were linear for RH and AH. The correlation for RH was modest ($r = 0.55$, $\beta = 0.39$). AH exhibited the strongest indoor-to-outdoor correlation ($r = 0.96$, $\beta = 0.69$).

Conclusions: Indoor and outdoor temperatures correlate well only at warmer outdoor temperatures. Outdoor RH is a poor indicator of indoor RH, while indoor AH has a strong correlation with outdoor AH year-round.

Keywords

temperature; humidity; exposure; indoor; outdoor; one-year measurement

INTRODUCTION

The climate is changing and will continue to for the next several decades (IPCC 2007). The range and extremes of ambient temperature are expected to change and regional weather patterns are anticipated to become more variable and more unstable (McMichael and Lindgren, 2011). A changing climate may present significant public health problems. Adverse health effects occur at both extreme (e.g., heat waves, cold spells) and less extreme ambient temperatures (Ye et al., 2012). The relationship between weather and human health is heterogeneous; the association varies by geography and is often J-shaped or U-shaped, with varying thresholds at which both cold-related and heat-related risks increase for different diseases (Bhaskaran et al., 2009; Ye et al., 2012), cardiovascular-related mortality (Medina-Ramon and Schwartz, 2007; Anderson and Bell, 2009; Braga et al., 2002), and all-

Corresponding Author Information: Jennifer L. Nguyen Phone: 617-384-8753 Fax: 617-432-6913 jln886@mail.harvard.edu.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

cause mortality (Medina-Ramon and Schwartz, 2007; Anderson and Bell, 2009; Hajat et al., 2007; McMichael et al., 2008).

Studies relating weather to health commonly use a single population-level indicator – an outdoor central site monitor - as an indicator of personal exposure. This approach may lead to misclassification of exposure that is likely more variable at the home or personal level (White-Newsome et al., 2012) due to individual differences in time-activity patterns and sources of exposure (e.g., local indoor, person-generated, and outdoor sources in homes and workplaces) (Rhomberg et al., 2011). Since people in industrialized countries generally spend more than 90% of their time indoors (Hoppe and Martinac, 1998), indoor conditions may be a better measure of personal exposure than outdoor measures. However, if indoor conditions correlate strongly with ambient outdoor conditions, using weather service observations of outdoor conditions would be a sufficient, practical indicator of personal exposure.

Commonly used weather measures in health studies are outdoor mean daily temperature, minimum and maximum temperature, and indices that combine air temperature and humidity, such as apparent temperature and the humidity index (Conlon et al., 2011; Ye et al., 2012). No single temperature measure has been reported to be the preferred measure for relating weather to human health (Barnett and Astrom, 2012). Further, few studies have examined how indoor temperature and humidity are related to outdoor, ambient levels. Characterization of this relationship would aid in understanding sources of measurement error in epidemiological studies.

The purpose of this study was to examine the relationship between indoor conditions to outdoor weather observations in Greater Boston, Massachusetts, USA. We focused on four weather measures – temperature, apparent temperature, relative humidity (RH), and absolute humidity (AH).

MATERIALS AND METHODS

Study population

The target population for this study was homes in Greater Boston, Massachusetts. In November 2010, occupants of potential participant homes were approached without prior knowledge of housing characteristics or indoor climate control. Participation was solicited from faculty and staff known to the study authors at the Harvard School of Public Health, and homes were eligible if the current occupants planned to remain in the same residence for at least 12 months and were able to exchange samplers for periodic data downloads. Of 25 persons contacted, four declined and four homes were ineligible because the occupants planned to move within the next year. Seventeen homes were enrolled. One home was excluded when the occupant left the Harvard School of Public Health in May 2011. Two homes were withdrawn from the study early because the occupants changed residence (one in October, one in December), but we retained their data. Occupants completed a brief questionnaire about their residence, including residence type (apartment or single family house), type of home heating system (baseboard, forced hot air, or radiator), cooling system (central air conditioning, window air conditioning or none), and use of a humidifier or de-humidifier.

Indoor measurements

Temperature (°C) and RH (%) was measured continuously from December 1, 2010 to April 30, 2012. Occupants were given one HOBO U8 Data Logger (H08-004-02 or H08-007-02, Onset Corporation; Bourne, Massachusetts) in late November 2010. These loggers measure temperature from -20°C to 70°C with accuracy of ± 0.7°C at 21°C and RH from 25% to

95% with accuracy ± 5%. The occupants were asked to place the data loggers in their living rooms away from sources of heat, cold, moisture and dryness. The loggers were brought to Harvard School of Public Health approximately every two months for data downloading. After initial examination of the data, the measurement range of the U8 loggers was found to be insufficient to capture low winter indoor RH (i.e., the U8 loggers could not measure RH below ~ 25%). Data recorded between December 2010 and April 2011 were discarded and the end of the study was extended to April 30, 2012. In September and October 2011, the U8 loggers were replaced with HOBO U12-011 Temperature and RH Data Loggers (Onset Corporation). Occupants were instructed to place the U12 logger in the same location where the U8 logger had been. These loggers measure temperature from -20°C to 70°C with accuracy of ± 0.35°C from 0°C to 50°C and RH from 5% to 95% with accuracy of ± 2.5% from 10% to 90%. The U12 loggers were calibrated once using National Institute of Standards and Technology instrumentation, EDGETECH Model DS2 Dew Point Hygrometer in a calibration environment of approximately 25°C and 50% RH. Ten loggers were calibrated in July 2011; the remaining 6 were calibrated in October 2011.

The U8 series of loggers recorded measurements at 24-minute intervals and the U12 loggers recorded measurements at 30-minute intervals. Daily averages for each home were computed only when all measurements on a given day were available. The daily indoor average was computed using measurements from at least ten homes. Otherwise, the daily indoor average was considered missing. Due to the schedule of data downloading, ten indoor daily averages are missing. Apparent temperature and AH were derived from the measured temperature and RH. Apparent temperature is a measure of perceived temperature that takes into account the effect of humidity (Steadman, 1979). Apparent temperature was calculated using the following formula (Zanobetti and Schwartz, 2005): apparent temperature = -2.653 + $(0.994 \times T_c) + (0.0153 \times T_d^2)$, where T_c is temperature in °C and T_d is dew point temperature in °C. RH is the proportion of water vapor in the air relative to the maximum water vapor that can be held in air at a given temperature, and thus a temperature-dependent measure. AH is a measure of the water vapor content in air expressed as a density (g/m^3). This metric is not functionally dependent on temperature (Mendell and Mirer, 2009).

Outdoor measurements

The daily outdoor, ambient temperature (°C), dew point temperature (°C), and RH (%) were obtained from the National Weather Service Station at Boston Logan Airport, East Boston, MA. Apparent temperature and AH values were computed from the temperature, RH, and dew point.

Statistical analysis

We calculated Pearson correlation coefficients (*r*) and 95% confidence intervals (CI) between the indoor and outdoor daily averages. We examined the shape of the relationships using linear, piecewise linear, and loess regression models. We tested for deviation from linearity using an approximate F-test comparing the linear model to the non-parametric loess regression model (Keele, 2008). Piecewise linear regression was fit using the "significant zero crossings" method, a non-parametric smoothing method that identifies the existence of a threshold based on where the function's derivatives change significantly (Sonderegger et al., 2009). We constructed boxplots comparing the magnitude and variability of home-specific daily correlations in the heating season (November - April) vs. the non-heating season (June - September), allowing for one transition month between seasons (May and October). We examined the spatial variation of the home-specific daily correlations using the Moran's I and Local Moran's I, measures of global and local spatial autocorrelation, respectively. For both spatial tests, Z-scores indicate the probability of autocorrelation. We found evidence of spatial variation for AH. We then assessed if distance to the Boston

NIH-PA Author Manuscript

NIH-PA Author Manuscript

airport and the ocean were significant predictors of the residential AH correlations. Because air conditioning was significantly associated with distance to the airport and coast, we adjusted for air conditioning (central, window, or none) using residuals from a logistic model. In sensitivity analyses, we examined the relationship between indoor and outdoor maximum and minimum daily average temperatures.

SAS version 9.2 (SAS Institute; Cary, North Carolina) was used to construct data sets and calculate descriptive statistics and correlation coefficients. R version 2.14.0 (R Foundation for Statistical Computing; Vienna, Austria) was used for regression modeling. The *Analyzing Patterns* and *Mapping Clusters* toolsets in ArcGIS v10.01 (ESRI; Redlands, California) were used for spatial analyses.

RESULTS

The 16 participating homes were located an average of 12.6 miles (20.3 km) from Boston Logan airport (range: 4.2, 26.4 miles, *Figure 1*). Twelve (75%) were single family homes, 11 (69%) had either central or window air conditioning, humidifiers were used in 4 (25%) homes and de-humidifiers were used in only 2 (12.5%) homes (*Table 1*).

Temperature, apparent temperature, and AH display a seasonal pattern both indoors and outdoors, with highs during the summer months. In contrast, indoor RH follows a similar seasonal pattern, but outdoor RH fluctuates with no consistent pattern (*Figure 2*). The average daily weather conditions from May 2011 – April 2012 are presented in Table 2. Correlation coefficients between the indoor and outdoor levels are provided in *Table 3*.

We found significant deviation from linearity for the relationship between indoor and outdoor temperature, apparent temperature, and AH (all p-values < 0.05), but not for RH. However, examination of the scatterplot for AH indicated that linear regression provided an adequate and parsimonious model fit (*Figure 3*). Piecewise linear regression identified a threshold of 12.7°C (54.9°F) for temperature and a threshold of 9.8°C (49.6°F) for apparent temperature. When outdoor temperatures are ≥ 12.7°C, there is a strong linear correlation with the average indoor temperature (r = 0.91, 95% CI: 0.89, 0.93, β = 0.41, standard error, se(β) = 0.02). The relationship is considerably weaker below this threshold (r = 0.40, 95% CI: 0.27, 0.52, β = 0.04, se(β) = 0.01). When outdoor apparent temperature is ≥ 9.8°C, there is a strong correlation with indoor apparent temperature (r = 0.94, 95% CI: 0.93, 0.96, β = 0.42, se(β) = 0.02). The correlation weakens below this threshold (r = 0.66, 95% CI: 0.57, 0.74, β = 0.09, se(β) = 0.01). The correlation for RH was modest (r = 0.55, 95% CI: 0.47, 0.62, β = 0.45, se(β) = 0.04). AH exhibited the strongest indoor-to-outdoor correlation (r = 0.96, 95% CI: 0.95, 0.97, β = 0.69, se(β) = 0.01).

In sensitivity analyses examining maximum and minimum temperature, results were similar to those for average temperature. Both weather metrics exhibited a piecewise linear relationship, with the threshold shifting to 15.6°C for maximum temperature and 9.8°C for minimum temperature. Similarly, the correlations were weak at lower outdoor temperatures (r = 0.16, 95% CI: 0.002, 0.31, β = 0.02, se(β) = 0.01 for maximum temperature; r = 0.64, 95% CI: 0.55, 0.72, β = 0.08, se(β) = 0.01 for minimum temperature), and stronger at warmer outdoor temperatures (r = 0.87, 95% CI: 0.84, 0.90, β = 0.40, se(β) = 0.02 for maximum temperature; r = 0.92, 95% CI: 0.89, 0.94, β = 0.49, se(β) = 0.02 for minimum temperature).

Correlations for all weather measures were lowest during the heating season (November – April). However, for AH, the magnitude remained strong and was similar to the variability observed in the non-heating season (June – September, *Figure 4*). Homes with a high (or low) correlation with one weather measure did not tend to have a high (or low) correlation with other weather measures. For example, the home with the lowest year-round absolute humidity correlation (r = 0.82) had the 5th highest year-round correlation for temperature (r = 0.86).

There was evidence of a spatial pattern in the home-specific daily AH correlations; correlations were significantly lower for homes located further west (Global Moran's Index = 0.24, Z-score = 3.65, $p < 0.0005$). Central air conditioning was significantly associated with distance to the airport ($p < 0.005$) and the coast ($p < 0.001$). Adjusting for air conditioning, the home-specific correlations significantly decreased with increasing distance from the Boston airport (p = 0.02, *Figure 5*) and from the ocean (β = - 0.003, p = 0.03). There was no significant pattern in the home-specific daily correlations for temperature (p = 0.16), apparent temperature (p = 0.91), or RH (p = 0.74).

DISCUSSION

Exposure measurement error is a common limitation of studies of the environment and health (Zeger et al., 2000). When measurements from a central site monitor, such as an airport weather station, are used to estimate personal exposures, the true exposure variability is underestimated (Rhomberg et al., 2011) and results in measurement error. Measurement error affects estimation of the exposure-response relationship by changing the apparent shape of the relationship, masks population-level thresholds, reduces statistical power (Rhomberg et al., 2011), and makes it difficult to interpret associations (Zeger et al., 2000). A better understanding of how indoor conditions vary with outdoor conditions would help in estimating the likelihood and magnitude of exposure measurement error.

In a sample of homes in eastern Massachusetts, we found that outdoor, airport AH is strongly correlated to indoor AH, which suggests that outdoor AH may be a good indicator of personal exposure to AH. Outdoor temperature and apparent temperature were strongly correlated to indoor temperatures only when outdoor temperatures were warmer. If our results can be extended to other areas, our findings suggest that studies that have reported associations of outdoor warm temperature with health are unlikely to be strongly affected by measurement error, and the results are reasonably interpretable as a temperature effect. In contrast, the weak correlation indoors-to-outdoors for temperature on cooler days suggests that outdoor temperature is a poor indicator of personal temperature exposure on cool days. Nevertheless, studies have reported associations between cold weather and increased morbidity and mortality. Given the high degree of measurement error, the reason for these significant effects needs further exploration. The high correlation between outdoor temperature and indoor AH we observed (r = 0.90) may provide an explanation. Cold effects reported in the literature might, at least in part, be reflecting an association with AH, since outdoor cold temperature is a better surrogate for lower indoor AH than for lower indoor temperature. Further studies need to examine this question in a wider range of climatic conditions.

The correlation between indoor and outdoor RH was weak and suggests that outdoor RH is not a good indicator of indoor RH exposure.

We measured temperature and humidity in the living room of 16 homes, but there could be room-to-room and floor-to-floor variations in temperature and humidity (Wallace et al., 2002; Collins, 1986). Individual measurements are also affected by the proximity to sources of heat and moisture, such as laundry, showers and cooking (Wallace et al., 2002). We instructed occupants to place the data loggers in a location away from such sources. Differences in personal behavior in indoor climate regulation may vary by season. For example, windows are more likely to be opened for extended periods of time when the outside temperature is moderate (Wallace et al., 2002). Systematic variation in the relationship between personal exposures and ambient levels at different times and in different locations can result in a classical-type error that biases exposure-response relationships (Rhomberg et al., 2011). Our results suggest that systematic variation is of concern for temperature, apparent temperature, and RH. Indoor AH, however, exhibited a strong correlation with outdoor levels year-round, in both the heating and non-heating seasons. This suggests that systematic variation is unlikely to be a significant source of measurement error when using AH as an exposure measure.

Homes with a high correlation for one weather measure did not tend to have a high correlation for other weather measures. Differences in thermal preferences, levels of temperature control, socioeconomic status, and the health states of the homes' occupants likely all contribute to this variability. In Boston, the cost of heat is generally included in the rent for apartments, and apartment renters may or may not be able to control the thermostat. In homes with accessible thermostats, thermal control and air conditioning use might increase with higher household wealth. Humidifiers are expected to be used more often in homes with occupants suffering from respiratory and/or skin ailments.

There was spatial variability in the correlation between indoor and outdoor AH. This finding was not surprising, since in the northeast United States, excursions of warm, moist air from the Gulf of Mexico provide the major source of moisture and lead to local spatial variability in AH (Robinson, 1998). Correlations weakened with increasing distance from the Boston airport. However, the decline with distance is small; a 30-mile increase in distance lowers the expected correlation by less than 10%. The observed pattern cannot be explained by dehumidifier use, which reduces indoor AH levels independent of temperature (Bernstein et al., 2005), because only one occupant residing further inland reported using a de-humidifier. Spatial variability in exposure is considered to be a Berkson-type error that is unlikely to bias measures of association in epidemiologic studies (Zeger et al., 2000).

Temperature and humidity affect the thermal balance of the human body through effects on the skin and respiratory organs (Reinikainen and Jaakkola, 2003). Changes in air temperature trigger a sympathethic reflex via the skin that strengthens with lower air temperature (Schneider et al., 2008). Exposure to cold increases plasma concentrations of norepinephrine and induces peripheral vasoconstriction via stimulation of alpha-adrenergic receptors. Vasoconstriction limits heat loss by redistributing blood to the core and causes an increase in cardiac output that supports higher metabolic production (Castellani et al., 2002). Cold extremities and the lowering of core body temperature can induce short-term increases in heart rate and blood pressure and promote increased blood viscosity (Collins, 1986), hemoconcentration and arterial thrombosis that could lead to triggering of acute cardiac events. Overexertion in a cold environment (e.g. shoveling snow) could trigger increases in blood pressure that lead to coronary plaque rupture and subsequent coronary thrombosis (Medina-Ramon and Schwartz, 2007). Redistribution of blood flow, reduced plasma volume, increased cardiac output, and activation of the sympathetic nervous system all affect components of the immune system. Leukocyte, granulocyte (Castellani et al., 2002) and macrophage (Larsson et al., 1998) counts increase after exposure to cold air, but whether cold exposure actually depresses immune function is still unclear (Castellani et al., 2002). High temperatures and humidity require the human body to respond by increasing heat loss through the skin surface via blood circulation (Hoppe and Martinac, 1998). Loss of salt and water in sweat results in hemoconcentration (Keatinge, 2002). This places strain on the cardiovascular and respiratory systems, and combined with increased blood viscosity and cholesterol levels may increase the risk of cardiovascular and respiratory deaths (Medina-Ramon and Schwartz, 2007).

AH is considered to be the most important measure of humidity for the estimation of the effect of humidity on the human body (Fielder, 1989). Separating the effects of cool air from dry air on the airways is difficult because cold air is necessarily dry. Isolating the effect of dry air by breathing warm, dry air is also insufficient because evaporative water loss causes cooling of the lungs (Giesbrecht, 1995). Inspired air is warmed to body temperature, saturated with water in the airways, and results in substantial heat and water loss in the larger airways (Larsson et al., 1998). In fact, increasing the water vapor content in inspired gas has the same biophysical consequences as warming of the airway mucosa (Fontanari et al., 1996). The degree of airway cooling and drying increases and moves to more central airways as the temperature and/or water content of the inspired air decreases (Giesbrecht, 1995). Cooling of the upper airways activates cold receptors or osmoreceptors in the nasal mucosa (Fontanari et al., 1996) that induce reflex-mediated bronchoconstriction (Koskela, 2007). Cold, dry air can promote respiratory infection by drying the mucosal surface (Reinikainen and Jaakkola, 2003) and decreasing the action of cilia that help to remove airway contaminants before they can be absorbed in the respiratory mucosa (Castellani et al., 2002; Collins, 1986).

The elderly are especially vulnerable to cold, dry air (Anderson and Bell, 2009; Hajat et al., 2007). Hemoconcentration resulting from peripheral vasoconstriction in response to cold weather makes blood more prone to clotting. Among the elderly, who often have roughened arteries by atheroma, this process increases the likelihood of thrombus formation. The loss of salt and water in sweat in response to hot temperatures may also increase the risk of clotting (Keatinge, 2002). Older persons have lower metabolic heat production and some develop disorders of thermoregulatory function. Debilitation and immunological senescence among older persons increases susceptibility to infectious diseases (Collins, 1986).

In general, people living in areas with higher mean temperatures are more vulnerable to cold days (Bhaskaran et al., 2009; The Eurowinter Group, 1997), though other studies have reported increased risk of mortality from colder weather in milder climates (Healy, 2003) and increased vulnerability to hotter temperatures in cities with milder warm seasons (Braga et al., 2002; Medina-Ramon and Schwartz, 2007). One explanation for this variability in health effects is differences in housing standards. For example, the Nordic countries of Sweden, Norway and Finland have very high home energy efficiency standards that aid in adapting to a comparatively cold climate, while homes in southern and western Europe have lower thermal efficiency (e.g., less insulation, fewer double-glazed windows) (Healy, 2003). Another possibility is that air conditioning use reduces the effect of temperature on health. Ostro et al. (2010) estimated a 0.76% absolute reduction in excess risk of cardiovascular disease for each 10% increase in air conditioner ownership for persons aged 65 years or older.

There are several limitations to this work. This study was limited by a small sample size and was confined to a small geographical area. Harvard faculty and staff may be different from the general population with respect to socioeconomic status, education, and knowledge on temperature and humidity as risk factors for adverse health outcomes, all of which may affect the level of temperature and humidity control of the home. The relationships found in this study may not be applicable to other regions due to community differences in the methods of climate adaptation (e.g., quality of housing, the prevalence of air conditioning, type and use of protective clothing) and the type of area (i.e., urban, suburban, or rural). Urban areas tend to be warmer than suburban and rural areas, due to increased heat retention in more heavily built-up and population-dense areas (Hajat et al., 2007). Finally, the relationships presented here cannot be directly linked to personal exposures due to differences in time-activity patterns within the home, movement between work, home, and the outdoors, and individual clothing preferences (Kim et al., 2011). These results apply to residential indoor exposure, and may not apply to indoor exposure experienced in settings such as work environments, office buildings and nursing homes.

Of four outdoor weather measures, we found that AH had the strongest correlation to indoor conditions. Examination of these relationships in other geographical locations could help explain why weather-related health risks have variable thresholds at which health effects occur at different geographical locations. Several studies have linked low AH levels to influenza-like illness, influenza epidemics and influenza-related mortality (Shaman et al., 2010; Shoji et al., 2011; van Noort et al., 2011), but few studies have examined AH exposure in relation to other health outcomes. Future epidemiologic studies of the association of weather with morbidity and mortality should include AH as a possibly better measure of exposure in terms of both measurement error and biological relevance.

Acknowledgments

We would like to thank all study volunteers for their participation. This study was supported in part by National Institute of Environmental Health Sciences (NIEHS) grant ES000002. J.L.N. received support from the Benjamin Greely Ferris, Jr. Fellowship Fund and NIEHS grants T32ES007069 and R21ES020194. JS received support from NIEHS R21ES020695 and NIA R21AG040027.

REFERENCES

Anderson BG, Bell ML. Weather-related mortality: how heat, cold, and heat waves affect mortality in the United States. Epidemiology. 2009; 20:205–213. [PubMed: 19194300]

Barnett AG, Astrom C. Commentary: What measure of temperature is the best predictor of mortality? Environ Res. 2012; 118:149–151. [PubMed: 22854320]

Bernstein JA, Levin L, Crandall MS, Perez A, Lanphear B. A pilot study to investigate the effects of combined dehumidification and HEPA filtration on dew point and airborne mold spore counts in day care centers. Indoor Air. 2005; 15:402–407. [PubMed: 16268830]

Bhaskaran K, Hajat S, Haines A, Herrett E, Wilkinson P, Smeeth L. Effects of ambient temperature on the incidence of myocardial infarction. Heart. 2009; 95:1760–1769. [PubMed: 19635724]

Braga AL, Zanobetti A, Schwartz J. The effect of weather on respiratory and cardiovascular deaths in 12 U.S. cities. Environ Health Perspect. 2002; 110:859–863. [PubMed: 12204818]

Castellani JW, M Brenner IK, Rhind SG. Cold exposure: human immune responses and intracellular cytokine expression. Med Sci Sports Exerc. 2002; 34:2013–2020. [PubMed: 12471310]

Collins KJ. Low indoor temperatures and morbidity in the elderly. Age Ageing. 1986; 15:212–220. [PubMed: 3751747]

Conlon KC, Rajkovich NB, White-Newsome JL, Larsen L, O'Neill MS. Preventing cold-related morbidity and mortality in a changing climate. Maturitas. 2011; 69:197–202. [PubMed: 21592693]

Fielder CP. Effect of weather conditions on acute laryngotracheitis. J Laryngol Otol. 1989; 103:187–190. [PubMed: 2926267]

Fontanari P, Burnet H, Zattara-Hartmann MC, Jammes Y. Changes in airway resistance induced by nasal inhalation of cold dry, dry, or moist air in normal individuals. J Appl Physiol. 1996; 81:1739–1743. [PubMed: 8904594]

Giesbrecht GG. The respiratory system in a cold environment. Aviat Space Environ Med. 1995; 66:890–902. [PubMed: 7487830]

Hajat S, Kovats RS, Lachowycz K. Heat-related and cold-related deaths in England and Wales: who is at risk? Occup Environ Med. 2007; 64:93–100. [PubMed: 16990293]

Healy JD. Excess winter mortality in Europe: a cross country analysis identifying key risk factors. J Epidemiol Community Health. 2003; 57:784–789. [PubMed: 14573581]

Hoppe P, Martinac I. Indoor climate and air quality. Review of current and future topics in the field of ISB study group 10. Int J Biometeorol. 1998; 42:1–7. [PubMed: 9780844]

IPCC. Climate change 2007: synthesis report.. In: Core Writing Team. Pachauri, RK.; Reisinger, A., editors. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. IPCC; Geneva, Switzerland: 2007. p. 104

Keatinge WR. Winter mortality and its causes. Int J Circumpolar Health. 2002; 61:292–299. [PubMed: 12546188]

Keele, L. Semiparametric regression for the social sciences. John Wiley & Sons, Ltd.; West Sussex, England: 2008.

Kim H, Chun C, Kwok A, Ota A, Tamura A. Cross-city comparison of indoor air temperatures in air-conditioned spaces. Indoor Air. 2011; 21:311–318. [PubMed: 21204990]

Koskela HO. Cold air-provoked respiratory symptoms: the mechanisms and management. Int J Circumpolar Health. 2007; 66:91–100. [PubMed: 17515249]

Larsson K, Tornling G, Gavhed D, Muller-Suur C, Palmberg L. Inhalation of cold air increases the number of inflammatory cells in the lungs in healthy subjects. Eur Respir J. 1998; 12:825–830. [PubMed: 9817153]

McMichael AJ, Lindgren E. Climate change: present and future risks to health, and necessary responses. J Intern Med. 2011; 270:401–413. [PubMed: 21682780]

McMichael AJ, Wilkinson P, Kovats RS, Pattenden S, Hajat S, Armstrong B, Vajanapoom N, Niciu EM, Mahomed H, Kingkeow C, Kosnik M, O'Neill MS, Romieu I, Ramirez-Aguilar M, Barreto ML, Gouveia N, Nikiforov B. International study of temperature, heat and urban mortality: the 'ISOTHURM' project. Int J Epidemiol. 2008; 37:1121–1131. [PubMed: 18522981]

Medina-Ramon M, Schwartz J. Temperature, temperature extremes, and mortality: a study of acclimatization and effect modification in 50 United States cities. Occup Environ Med. 2007; 64:827–833. [PubMed: 17600037]

Mendell MJ, Mirer AG. Indoor thermal factors and symptoms in office workers: findings from the US EPA BASE study. Indoor Air. 2009; 19:291–302. [PubMed: 19302503]

Ostro B, Rauch S, Green R, Malig B, Basu R. The effects of temperature and use of air conditioning on hospitalizations. Am J Epidemiol. 2010; 172:1053–1061. [PubMed: 20829270]

Reinikainen LM, Jaakkola JJ. Significance of humidity and temperature on skin and upper airway symptoms. Indoor Air. 2003; 13:344–352. [PubMed: 14636228]

Rhomberg LR, Chandalia JK, Long CM, Goodman JE. Measurement error in environmental epidemiology and the shape of exposure-response curves. Crit Rev Toxicol. 2011; 41:651–671. [PubMed: 21823979]

Robinson P. Monthly variations of dew point temperature in the coterminous United States. Int J Climatol. 1998; 18:1539–1556.

Schneider A, Schuh A, Maetzel FK, Ruckerl R, Breitner S, Peters A. Weather-induced ischemia and arrhythmia in patients undergoing cardiac rehabilitation: another difference between men and women. Int J Biometeorol. 2008; 52:535–547. [PubMed: 18228048]

Shaman J, Pitzer VE, Viboud C, Grenfell BT, Lipsitch M. Absolute humidity and the seasonal onset of influenza in the continental United States. PLoS Biol. 2010; 8:e1000316. [PubMed: 20186267]

Shoji M, Katayama K, Sano K. Absolute humidity as a deterministic factor affecting seasonal influenza epidemics in Japan. Tohoku J Exp Med. 2011; 224:251–256. [PubMed: 21705850]

Sonderegger D, Wang H, Clements W, Noon B. Using SiZer to detect thresholds in ecological data. Front Ecol Environ. 2009; 7:190–195.

Steadman R. The assessment of sultriness. Part I: a temperature-humidity index based on human physiology and clothing science. J Appl Meteorol. 1979; 18:874–885.

The Eurowinter Group. Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe. Lancet. 1997; 349:1341–1346. [PubMed: 9149695]

van Noort SP, Aguas R, Ballesteros S, Gomes MG. The role of weather on the relation between influenza and influenza-like illness. J Theor Biol. 2011; 298C:131–137. [PubMed: 22214751]

Wallace LA, Emmerich SJ, Howard-Reed C. Continuous measurements of air change rates in an occupied house for 1 year: the effect of temperature, wind, fans, and windows. J Expo Anal Environ Epidemiol. 2002; 12:296–306. [PubMed: 12087436]

White-Newsome JL, Sanchez BN, Jolliet O, Zhang Z, Parker EA, Dvonch JT, O'Neill MS. Climate change and health: indoor heat exposure in vulnerable populations. Environ Res. 2012; 112:20–27. [PubMed: 22071034]

Ye X, Wolff R, Yu W, Vaneckova P, Pan X, Tong S. Ambient temperature and morbidity: a review of epidemiological evidence. Environ Health Perspect. 2012; 120:19–28. [PubMed: 21824855]

Zanobetti A, Schwartz J. The effect of particulate air pollution on emergency admissions for myocardial infarction: a multicity case-crossover analysis. Environ Health Perspect. 2005; 113:978–982. [PubMed: 16079066]

Zeger SL, Thomas D, Dominici F, Samet JM, Schwartz J, Dockery D, Cohen A. Exposure measurement error in time-series studies of air pollution: concepts and consequences. Environ Health Perspect. 2000; 108:419–426. [PubMed: 10811568]

Practical Implications

This study examined the relationship between indoor and outdoor ambient weather conditions using four different measures. The results suggest that when only outdoor data are available for human weather exposure, absolute humidity is the outdoor measure least prone to measurement error. The results also show that outdoor temperature is a poor indicator of indoor temperature exposure during colder months in the New England region, USA. Studies relating outdoor weather to human health should take into consideration how well outdoor conditions serve as indicators of indoor or personal weather exposure in the studied geographical area.

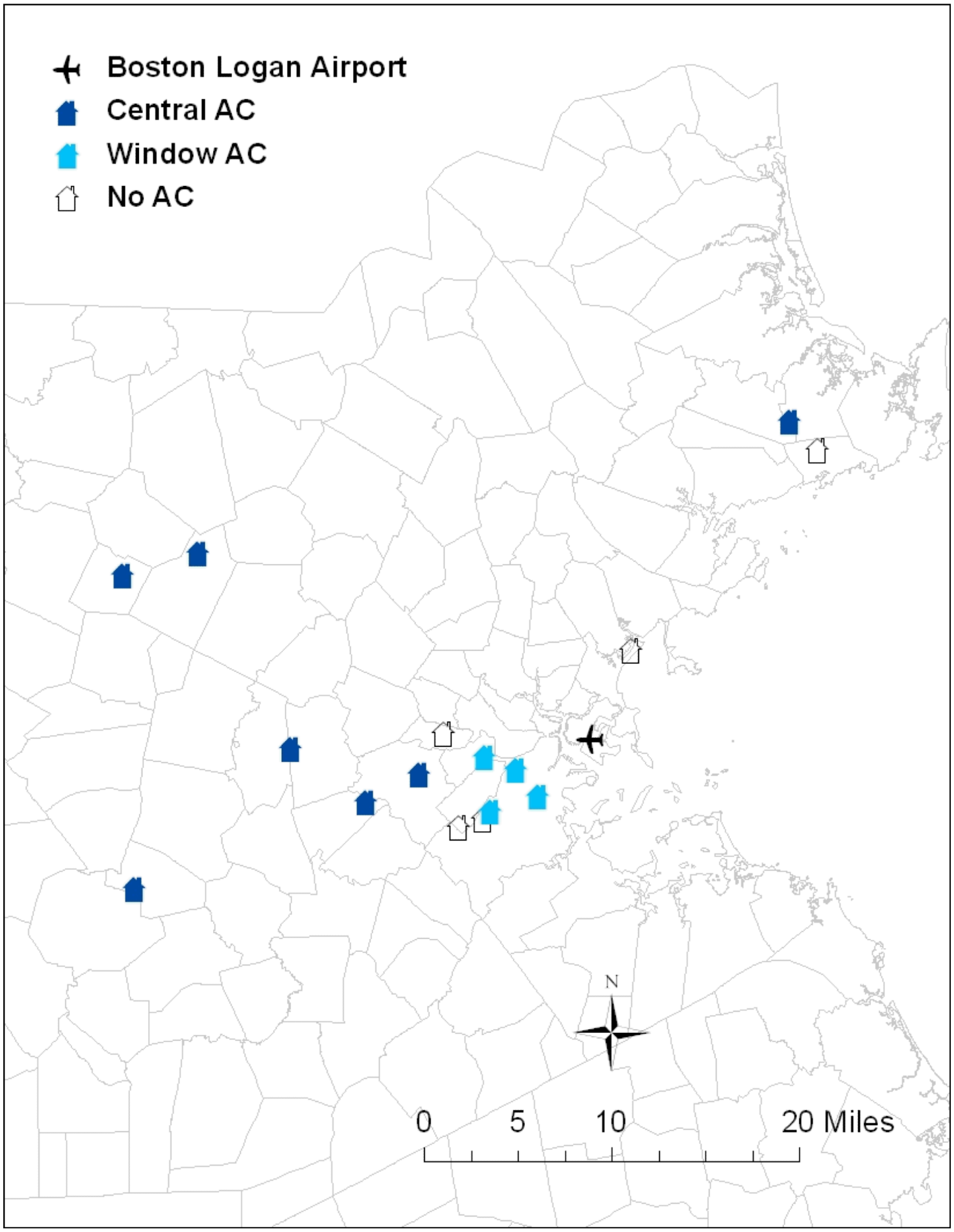


Figure 1.
Map of participant residences by air conditioning (AC) type and Boston Logan Airport, Massachusetts.

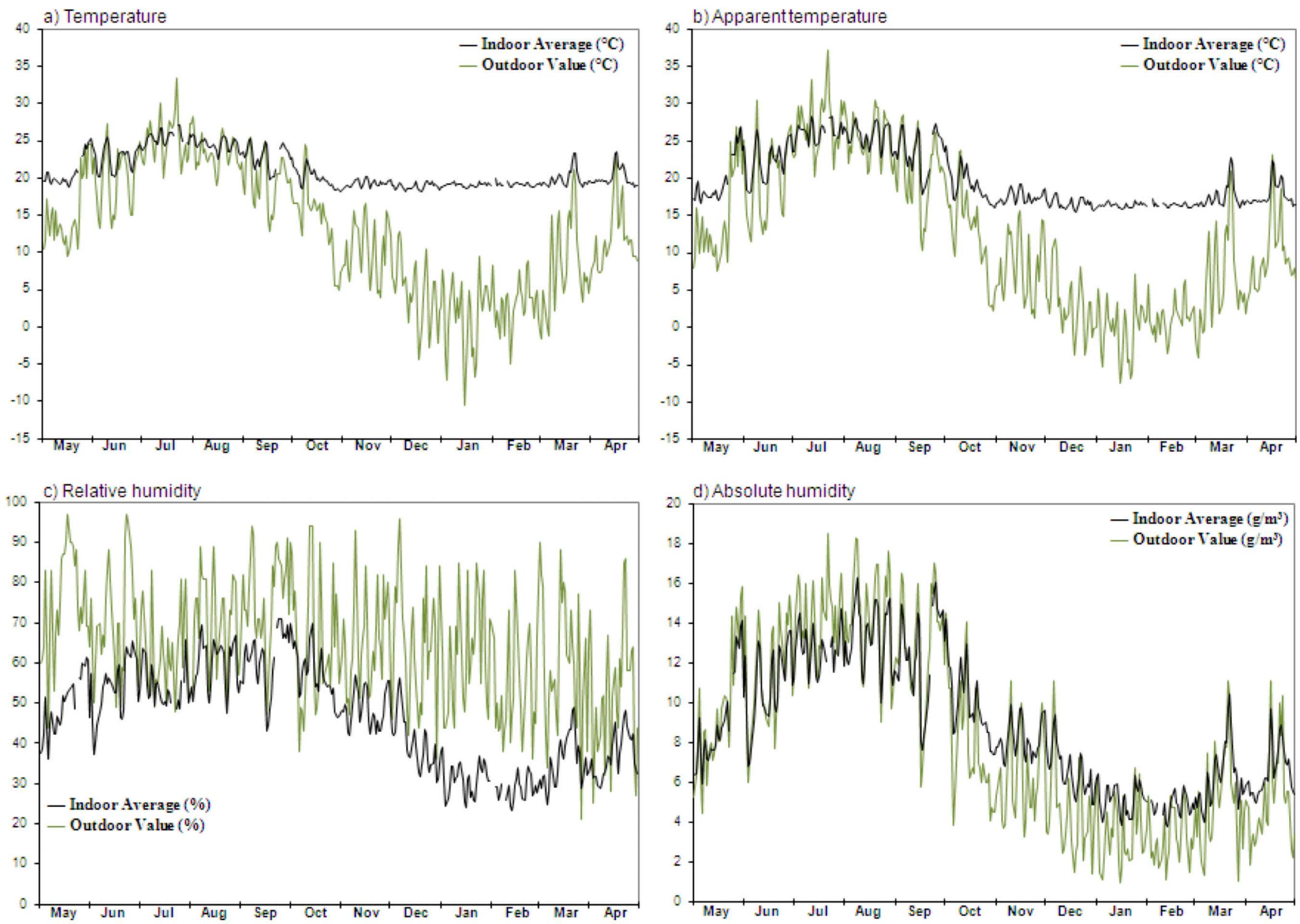


Figure 2.
Plot of indoor and outdoor daily (a) temperature, (b) apparent temperature, (c) relative humidity, and (d) absolute humidity from May 2011 – April 2012, Greater Boston, Massachusetts.

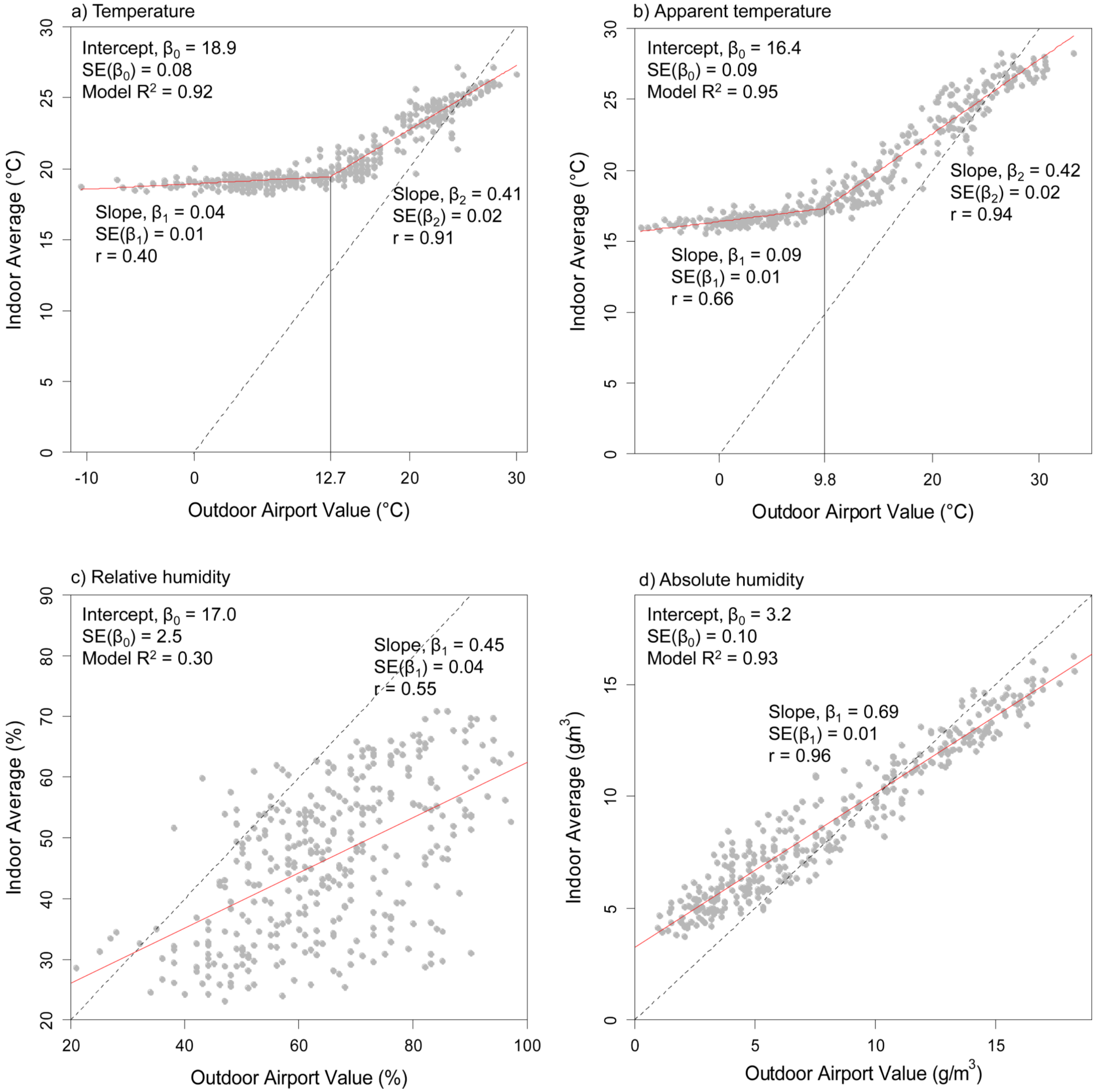
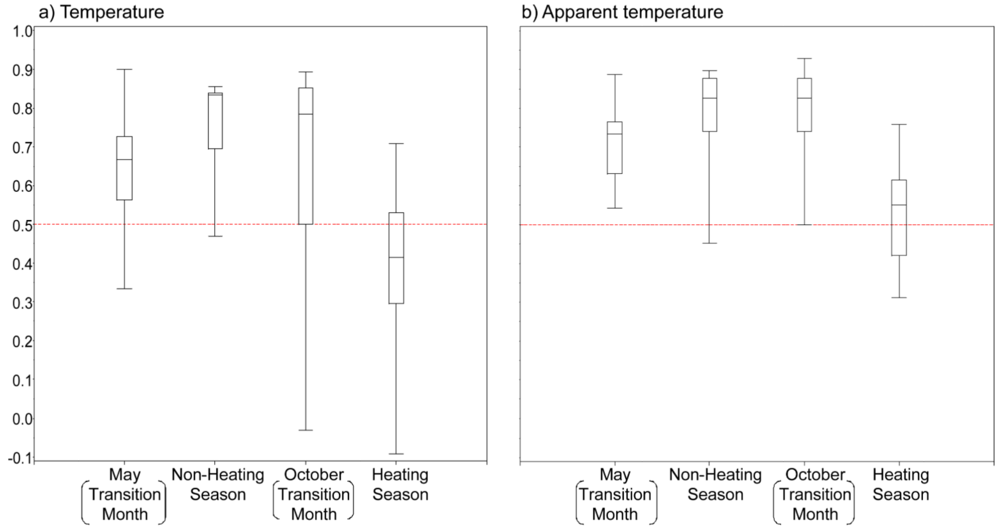


Figure 3.

Scatterplot and regression results relating indoor to outdoor (a) temperature, (b) apparent temperature, (c) relative humidity, and (d) absolute humidity from May 2011 – April 2012, Greater Boston, Massachusetts. Red line, piecewise linear regression for (a) and (b) and linear regression for (c) and (d); black solid line, reference line placed at knot value; black dashed line, y=x (45 degree) reference line. SE, standard error; r, correlation.

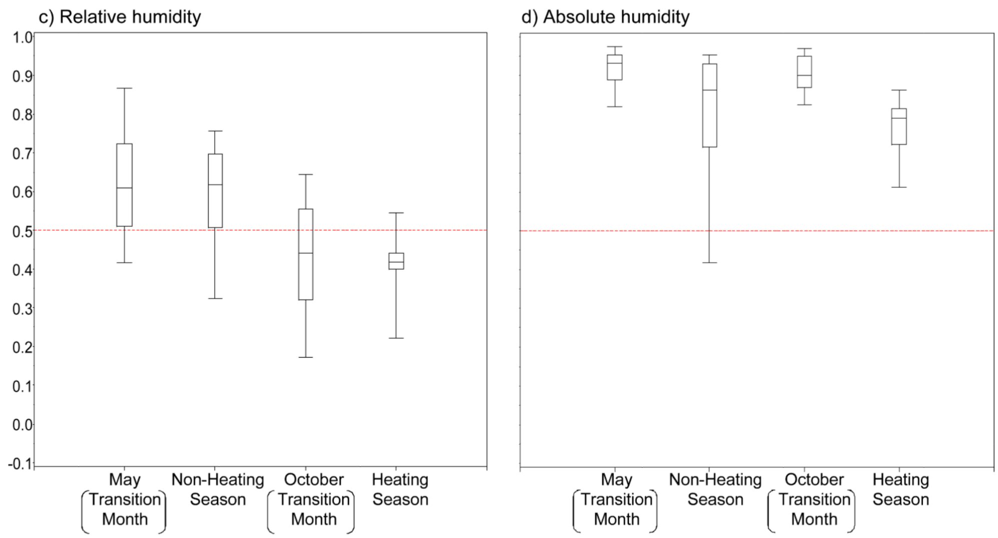


a) Temperature

	May Transition Month	Non-Heating Season	October Transition Month	Heating Season
Max	0.90	0.86	0.89	0.71
Q3	0.73	0.84	0.85	0.53
Median	0.67	0.83	0.79	0.41
Q1	0.56	0.69	0.50	0.30
Min	0.33	0.47	-0.03	-0.09

b) Apparent temperature

	May Transition Month	Non-Heating Season	October Transition Month	Heating Season
Max	0.89	0.90	0.93	0.76
Q3	0.76	0.88	0.88	0.61
Median	0.73	0.83	0.83	0.55
Q1	0.63	0.74	0.74	0.42
Min	0.54	0.45	0.50	0.31



c) Relative humidity

	May Transition Month	Non-Heating Season	October Transition Month	Heating Season
Max	0.87	0.76	0.64	0.55
Q3	0.72	0.70	0.55	0.44
Median	0.61	0.62	0.44	0.42
Q1	0.51	0.51	0.32	0.40
Min	0.42	0.32	0.17	0.22

d) Absolute humidity

	May Transition Month	Non-Heating Season	October Transition Month	Heating Season
Max	0.97	0.95	0.97	0.86
Q3	0.95	0.93	0.95	0.81
Median	0.93	0.86	0.90	0.79
Q1	0.89	0.72	0.87	0.72
Min	0.82	0.42	0.82	0.61

Figure 4.

Boxplots of the variability in residential indoor-to-outdoor correlations by heating season among 16 homes for (a) temperature, (b) apparent temperature, (c) relative humidity, and (d) absolute humidity from May 2011 – April 2012, Greater Boston, Massachusetts. Red dashed line placed for reference at correlation coefficient = 0.5. Top whisker, maximum; bottom whisker, minimum.

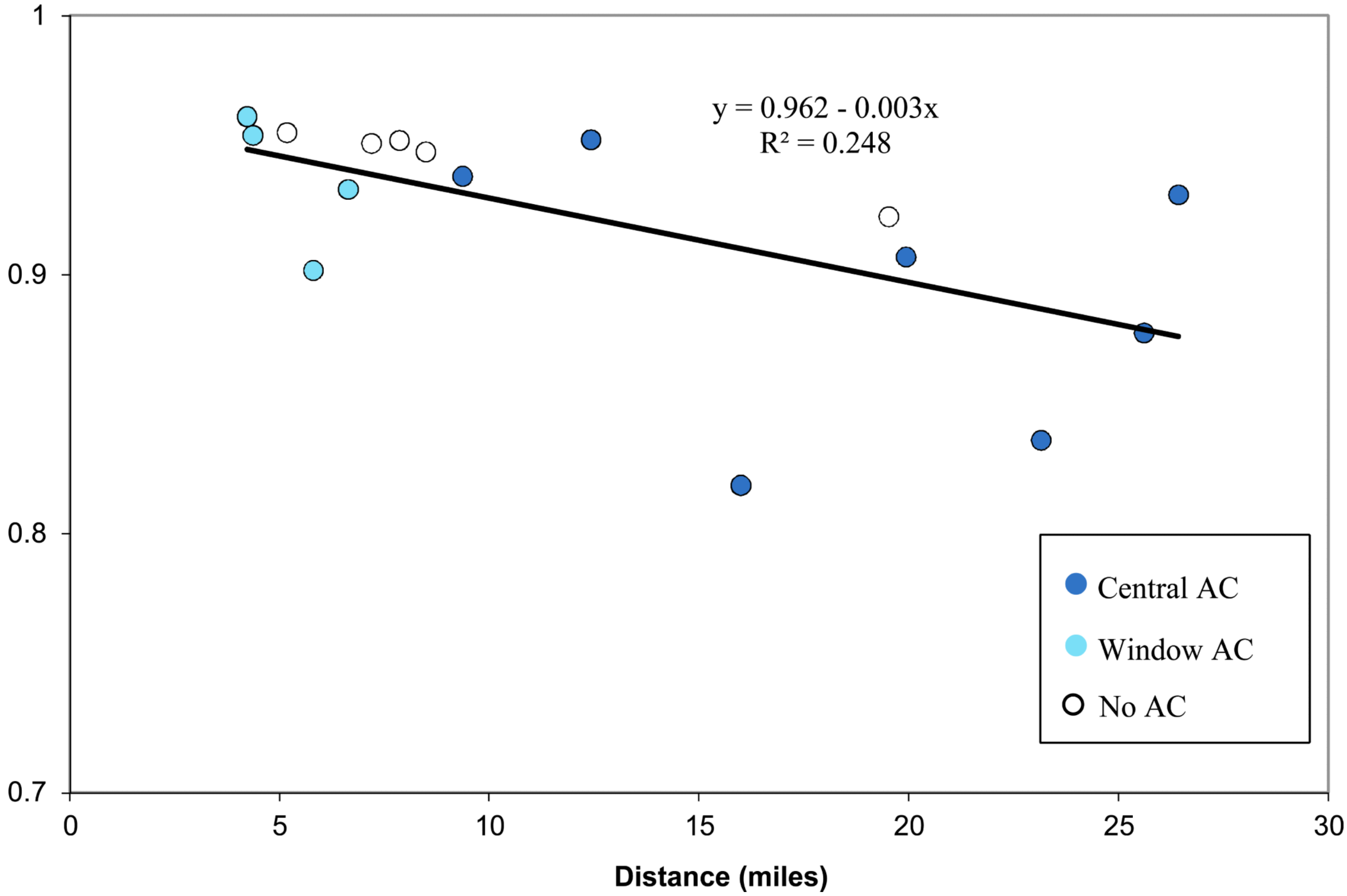


Figure 5.
Scatterplot and linear regression of home-specific indoor absolute humidity correlations to Boston Logan Airport in relation to distance to the airport from May 2011 – April 2012, Greater Boston, Massachusetts. Results are adjusted for air conditioning type.

Table 1

Indoor climate control characteristics of 16 homes in Greater Boston, Massachusetts.

Characteristic	N (%)
Residence Type	
Apartment	4 (25.0)
Single family house	12 (75.0)
Heating System	
Baseboard	5 (31.3)
Forced hot air	6 (37.5)
Radiator	5 (31.3)
Cooling System	
Central air conditioning	7 (43.8)
Window air conditioning	4 (25.0)
None	5 (31.3)
Use of a humidifier	
Yes	4 (25.0)
No	12 (75.0)
Use of a de-humidifier[1]	
Yes	2 (12.5)
No	14 (87.5)

[1]Excluding air conditioners

Table 2

Distribution of daily average outdoor and indoor temperature and humidity in Greater Boston, Massachusetts, May 2011 – April 2012

Measure	N	Mean (SD)	Min	25%	Median	75%	Max
Temperature (°C)							
Outdoor	366	13.1 (8.6)	-10.6	6.1	13.3	20.6	33.3
Indoor	356	21.0 (2.4)	18.2	19.2	19.8	23.4	27.2
Apparent Temperature (°C)							
Outdoor	366	12.4 (10.1)	-7.4	3.5	11.6	21.8	37.1
Indoor	356	19.9 (3.9)	15.5	16.7	18.0	23.5	28.3
Relative Humidity (%)							
Outdoor	366	64.8 (14.8)	21.0	54.0	65.0	76.0	97.0
Indoor	356	46.4 (12.2)	23.3	35.0	47.5	55.5	71.0
Absolute Humidity (g/m^3)							
Outdoor	366	8.2 (4.6)	0.9	4.2	7.3	12.3	18.5
Indoor	356	8.9 (3.2)	3.8	5.9	8.2	11.6	16.3

Table 3

Pearson correlation coefficients[1] for daily average outdoor and indoor temperature and humidity in Greater Boston, Massachusetts, May 2011 – April 2012

	Indoor			
Outdoor	**Temperature**	**Apparent Temperature**	**Relative Humidity**	**Absolute Humidity**
Temperature (°C)	0.87	0.89	0.80	0.90
Apparent Temperature (°C)	0.92	0.94	0.81	0.92
Relative Humidity (%)	0.20	0.30	0.55	0.45
Absolute Humidity (g/m^3)	0.88	0.93	0.88	0.96

[1] All p-values < 0.0001