Socioeconomic and Outdoor Meteorological Determinants of Indoor Temperature and Humidity in New York City Dwellings*

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ABSTRACT

Numerous mechanisms link outdoor weather and climate conditions to human health. It is likely that many health conditions are more directly affected by indoor rather than outdoor conditions. Yet, the relationship between indoor temperature and humidity conditions to outdoor variability, and the heterogeneity of the relationship among different indoor environments are largely unknown. The authors use 5–14-day measures of indoor temperature and relative humidity from 327 dwellings in New York City New York, for the years 2008–11 to investigate the relationship between indoor climate, outdoor meteorological conditions, socioeconomic conditions, and building descriptors. Study households were primarily middle income and located across the boroughs of Brooklyn, Queens, Bronx, and Manhattan. Indoor temperatures are positively associated with outdoor temperature during the warm season and study dwellings in higher socioeconomic status neighborhoods are significantly cooler. During the cool season, outdoor temperatures have little effect on indoor temperatures; however, indoor temperatures can range more than 10°C between dwellings despite similar outdoor temperatures. Apartment buildings tend to be significantly warmer than houses and dwellings on higher floors are also significantly warmer than dwellings on lower floors. Outdoor specific humidity is positively associated with indoor specific and relative humidity, but there is no consistent relationship between outdoor and indoor relative humidity. In New York City, the relationship between indoor and outdoor temperature and humidity conditions varies significantly between dwellings. These results can be used to inform studies of health outcomes for which temperature or humidity is an established factor affecting human health. The results highlight the need for more research on the determinants of indoor climate.

1. Introduction

Numerous studies link weather and climate conditions to human health outcomes (Tamerius et al. 2007). In many cases, however, the mechanisms responsible for the linkage between specific health outcomes, weather, and climate are not clearly understood. A more comprehensive

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understanding of these mechanisms is required to mitigate current environmentally mediated health risks, and predict the effects of future climate and environmental change on human welfare (Ebi et al. 2006).

Associations between temperature and morbidity and mortality rates have been well established (Kovats and Hajat 2008; Anderson and Bell 2009). In particular, several studies have shown a bimodal relationship between temperature and mortality (Anderson and Bell 2009; Goldberg et al. 2011; Liu et al. 2011), with significant increases in cardiovascular, respiratory and cerebrovascular deaths in both cold and warm temperatures (Conlon et al. 2011). Additionally, there are strong links between humidity and human health. For example, relative humidity affects the skin latent heat loss due to the evaporation of sweat (Campbell and Norman 1998) and high levels of relative humidity in combination with high temperatures have been shown to exacerbate respiratory and cardiovascular disease (Lin et al. 2009). Absolute humidity has been shown to affect the survival and transmission efficiency of influenza viruses (Shaman and Kohn 2009), and is associated with the onset of influenza epidemics in temperate regions such as the United States (Shaman et al. 2010).

Investigations of the mechanisms linking climate and weather to human health typically employ outdoor weather and climate observations (Conlon et al. 2011). Given that individuals in the United States spend approximately 90% of their time indoors (Klepeis et al. 2001), and this apportionment of time indoors is likely representative for much of the developed world (Schweizer et al. 2007), it stands to reason that indoor climate conditions may exert a greater influence on risk for many health conditions (White-Newsome et al. 2012; Smargiassi et al. 2008). It is also a possibility that observed geographic and demographic differences in climate–health relationships across latitude, socioeconomic status, and age (Chen et al. 2010; Conlon et al. 2011), may be due in part to differences in the management of indoor climate (The Eurowinter Group 1997).

At present, the response of indoor temperature and humidity conditions to outdoor variability, and the heterogeneity of that response among different indoor environments are largely unknown (Jendritzky and Dear 2009; White-Newsome et al. 2012). The predominant use of outdoor weather and climate data for studying human health outcomes is likely due to the widespread availability of such data and the relative paucity of existing indoor environmental data records. Here we investigate the associations between outdoor and indoor temperature and humidity for 327 middle-income dwellings across New York City, New York (NYC), and determine how these outdoor–indoor relationships vary by household and neighborhood level indicators of socioeconomic status (SES), and the social and built environment.

2. Data and methods

The New York City Neighborhood Asthma and Allergy Study (NAAS) is a case-control study of asthma that included a home visit to assess environmental exposures, a detailed questionnaire to asses health, environmental exposures and demographics, and the use of a comprehensive geospatial database to characterize the built-in and social environments surrounding the participants homes (Olmedo et al. 2011; Cornell et al. 2012). Participating households were those with children from ages 7–8 years and were insured through the Health Insurance Plan of New York, which primarily provides services to middle-income populations. Individual study households were selected from locations in the NYC boroughs of Brooklyn, Queens, Bronx, and Manhattan.

As part of the NAAS protocol, temperature and relative humidity were monitored for 5–14 days in 327 individual dwellings during the study period of March 2008 through June 2011. The timing of site visits was based on the birth date of the children in the participating study and accessibility to households. Temperature (T; dry bulb) and relative humidity (RH) conditions were recorded at 10-min intervals using HOBO U10 data recorders, which were placed by researchers in the living room at a height of 1.5 m. These data recorders have an accuracy of $\pm 0.53°C$ and $\pm 3.5\%$ for temperature and relative humidity, respectively. The data recorders were not placed near windows, radiators, or air conditioners. Indoor specific humidity (SH) was calculated from the indoor temperature and relative humidity, in combination with outdoor air pressure data from the North American Land Data Assimilation System (NLDAS) dataset (Mitchell et al. 2004; see supplementary material for equations). Indoor temperature and humidity records were quality inspected prior to use in this study. Spurious measurements at the end of a record most likely associated with the removal of a data recorder from its monitoring site were eliminated. The employed data recorders had a lower operating threshold of $\sim 25\%$ for relative humidity; consequently, the primary humidity analyses were limited to periods when outdoor specific humidity was greater than 10 g kg^{-1} (few dwellings dropped below 25% in these conditions). For dwellings where RH dropped below 25%, the mean indoor humidity (relative and specific) were calculated based on a minimum RH of 25%, thus, the true values are likely lower. The humidity threshold issue did not affect the temperature observations because the temperature and humidity sensors operate independently, and temperatures remained within the working limits of the sensors. However, a few anomalously high readings (greater than 40°C), which were likely caused by sensor malfunction or placement in a location receiving direct sunlight, were also removed. After elimination of these erroneous observations, the remaining temperature and humidity data were averaged for each dwelling. This resulted in a total of 326 temperature and 159 humidity observations.

Two outdoor temperature and humidity data sources were acquired for this study. Hourly outdoor specific humidity, temperature (dry bulb), and surface pressure data for 2008–11 were obtained from the NLDAS for NYC (pixel centered at 40.813°N, −73.938°E). Hourly relative humidity was then calculated from the SH, T, and pressure data using appropriate thermodynamic relationships (Wallace and Hobbs 2006; see supplementary material for equations). Mean daily dewpoint and temperature data for 2008–11 were also acquired from National Oceanic and Atmospheric Association (NOAA) station records for John F. Kennedy and LaGuardia International Airports in NYC. Mean daily RH and SH were then calculated from these dewpoint and temperature data. The outdoor temperature and humidity data were averaged for the time periods corresponding to the indoor observation periods for each of the 326 and 159 study dwellings, respectively, for both the NLDAS and the NOAA station data. We examined the consistency of the two outdoor datasets used in this study and found that the temperature, specific humidity and relative humidity data were significantly correlated ($p < 0.0001$), with Pearson's correlation coefficients (r) equal to 0.99, 0.99, and 0.84, respectively. Because the data are so similar, we report only the results of the averaged station data herein for simplicity.

We also related indoor conditions to variables at the household, building, and neighborhood level (Table 1 and Supplementary Fig. S1). For neighborhood level SES indicators, we used median income, rates of poverty, population density, and fraction of rented (versus owned) households obtained from the U.S. Census Bureau (2007). Each household was assigned the characteristics of the surrounding census block groups within a 0.25-km buffer. Census block groups that were not completely contained by the buffer were apportioned according to the fraction of their area within the buffer. The year that construction was completed for the building of each study dwelling was obtained from the City of New York Department of City Planning. Additional dwelling and building descriptor data were generated from the NAAS study survey and provided information regarding household income, dwelling condition (e.g., water damage), material hardship (e.g., difficulty in paying bills), dwelling floor level, and building type (apartment or house). Since approximately 10% of participants failed to report household income, we dropped this variable from the primary regression analysis. The effects of geographical variables such as borough, latitude, longitude, and elevation were also investigated. Several variables related to socioeconomic status were highly collinear (see Supplementary Fig. S1). Some household information that would have proved informative for the purposes of this study (e.g., air conditioning use) was not available given that the surveys were not designed specifically for the purpose of examining relationships between outdoor and indoor climate.

TABLE 1. List of independent variables and their units and categories employed in this study.

Variable	Units/categories
Indoor specific humidity	g kg^{-1}
Indoor temperature	°C
Indoor relative humidity	%
Longitude	°
Latitude	°
Floor of home	No.
Building type	Apartment/house
Floors in the building	No.
Borough	Manhattan/Bronx/Brooklyn/ Queens
Poverty (0.25-km radius)	%
Median household income (0.25-km radius)	$
Rented households (0.25-km radius)	%
Vacant households (0.25-km radius)	%
Year residence was built	Year
Park area (0.25-km radius)	%
Rooms in household	No.
Basement in building	Yes/no
Water damage in household	Yes/no
Race	Black/Asian/white/ American Indian/ South Asian/other
Income	$
Material hardship	Yes/no
Elevation	Meters

Initial exploratory analysis indicated that the relationship between indoor and outdoor temperature was not consistent. We applied a segmented regression method (Jones and Molitoris 1984) to characterize this relationship between indoor and outdoor temperature. Specifically, two regressions were performed at all possible intervals (without overlap) across the domain of the independent variable (i.e., outdoor temperature). We calculated the residual sum of squares (RSS) for each of the regression pairs and defined the breakpoint

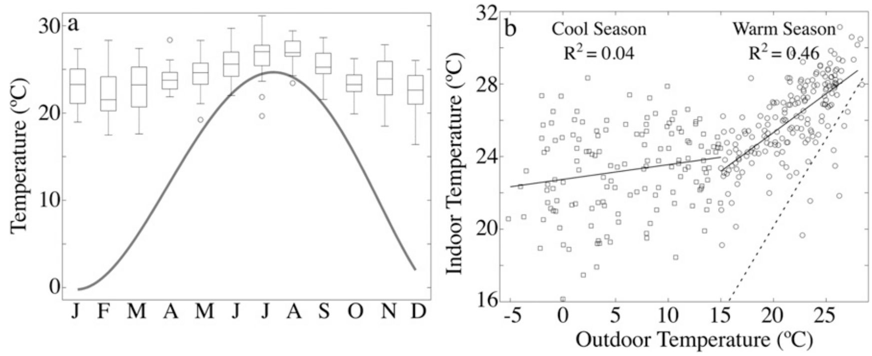

FIG. 1. (a) The seasonal variation of indoor temperature (box plots) and outdoor temperature (line plot). The plot highlights the minimal seasonal indoor temperature variability compared to outdoor temperature variability. (b) The relationship between indoor and outdoor temperature without a temporal component. The dotted line indicates the points at which indoor and outdoor temperature are equal. When outdoor temperature is less than 15°C (squares), the mean indoor temperature increases by only 0.06°C for every 1°C increase outdoors. During the warm season when the outdoor temperature is greater than 15°C (circles), the mean indoor temperatures increase 0.43°C for every 1°C increase outdoors.

as the outside temperature that corresponded to the minimum RSS.

We generated general linear models (GLM) to identify the best predictors of indoor temperature, relative humidity, and specific humidity. A model selection procedure was developed to determine the best individual predictor and groups of predictors, with all possible univariate, bivariate, and trivariate GLMs generated for each of the outcome variables. Only models in which each predictor was significant ($p < 0.05$) were retained. The Akaike information criterion with a second-order bias correction (AICc) was calculated (Burnham and Anderson 2004) and used to judge the relative goodness of fit among retained models. The stability of each model was evaluated by applying the models across strata of outdoor temperature and humidity conditions.

3. Results

a. Indoor temperature

Outdoor temperature was a strong predictor of indoor temperature ($r = 0.62$, $p < 0.0001$); however, the strength of this relationship differs for warm and cool seasons (Fig. 1). Segmented regression indicated that a breakpoint occurs at approximately 15°C (the boundary between the two segments), although the RSS is comparable for outdoor temperatures of 12°–17°C. An F test shows that using the segmented regression with a breakpoint at 15°C provides a significantly ($p < 0.0001$) better fit than a single regression across the entire domain (Fig. 1).

During the warm season (outdoor temperatures greater than 15°C), average dwelling temperature ranged from 19.7° to 31.1°C, with a mean of 26.3°C (Table 2). Outdoor temperature was the single best predictor of indoor temperatures ($r = 0.68$, $p < 0.0001$); temperatures increased by 0.43°C for every 1°C increase outdoors. Outdoor specific humidity was the second-best predictor of indoor temperature ($r = 0.60$, $p < 0.0001$), which was expected given the strong relationship between outdoor temperature and specific humidity ($r = 0.97$, $p < 0.0001$).

The best multivariate model for indoor temperatures during the warm season included outdoor temperature, the number of rooms in the dwelling, and whether or not water damage was reported (Table 3). Each added room

TABLE 2. A summary of the indoor and outdoor temperature and humidity observations. The values in parentheses correspond to the 10th and 90th percentiles.

	No. of observations	Duration of monitoring (days)	Indoors	Outdoors
Mean temperature (°C)	326	10.2 (7.0 13.0)	24.9 (21.2 28.2)	14.9 (1.1 25.4)
Mean specific humidity (g kg^{-1})	118*	10.1 (7.0 13.0)	9.6 (7.2 12.0)	11.7 (7.1 15.1)
Mean relative humidity (%)	118*	10.1 (7.0 13.0)	47.1 (39.6 55.6)	73.6 (66.6 82.3)

* The number of humidity observations remaining after dropping observations with mean outdoor specific humidity less than 10 g kg^{-1} or below 25% RH.

TABLE 3. Coefficients (and 95% confidence intervals) for the five best multivariate linear models for indoor temperature (°C), while outdoor temperatures are greater than 15°C. The coefficients for univariate models for each of the variables present in the multivariate models are included in the first column.

$n = 172$	Bivariate	Model 1	Model 2	Model 3	Model 4	Model 5
AICc	—	145.20	148.40	149.40	149.90	150.40
Outdoor temperature	0.44[a] (0.36 0.51)	0.41[a] (0.34 0.48)	0.40[a] (0.33 0.47)	—	0.42[a] (0.38 0.53)	0.40[a] (0.33 0.47)
No. of rooms in household	−0.19 (0.38 0.01)	−0.26[b] (−0.40 0.12)	—	−0.25[b] (−0.39 −0.11)	−0.25[b] (−0.39 −0.11)	—
Water damage	−0.91[c] (−1.62 −0.19)	−0.70 (−1.24 −0.17)	−0.73[c] (−1.27 −0.19)	—	—	−0.69 (−1.23 −0.15)
Median household income in neighborhood (by $10,000)	−0.25 (−0.47 −0.19)	—	−0.27[c] (−0.45 −0.11)	—	—	—
Outdoor specific humidity	0.56[a] (0.43 0.70)	—	—	0.60[a] (0.49 0.72)	—	—
Outdoor relative humidity	−0.14[a](−0.18 −0.09)	—	—	−0.08[a] (−0.12 −0.05)	—	—
% of rentals in neighborhood	0.01 (0.00 0.03)	—	—	—	—	0.01[c] (0.00 0.02)

[a] $p = 0.0001$.
[b] $p = 0.001$.
[c] $p = 0.01$.

in a dwelling was associated with a 0.27°C decrease in indoor temperature and households reporting water damage was associated with a 0.76°C decrease. Several other models that included various permutations of outdoor temperature, relative humidity, specific humidity, water damage, number of rooms in the dwelling, and median household income in the neighborhood had similar AICc scores (Table 3). The number of rooms in the dwelling and the median household income in the neighborhood are significantly associated with income in the study household ($p < 0.001$) (Supplementary Fig. S1). Yet, when we perform regressions on the subset of households that reported income we find that the number of rooms in the dwelling and the median neighborhood income are stronger predictors of indoor temperature than household income. It should also be noted that, unlike the cool season (see below), the floor level of the dwelling was not a significant predictor of indoor temperature ($p = 0.90$).

During the cool season (outdoor temperature is less than 15°C) average dwelling temperatures ranged from 16.1° to 28.3°C, with a mean of 23.2°C (Table 2). Although the coolest indoor temperatures coincided with the coldest outdoor temperatures, mean indoor temperatures in several study dwellings remained greater than 25°C even as mean outdoor temperatures decreased to 0°C (Fig. 1). The relationship between indoor and outdoor temperatures was considerably weaker than it was during the warm season ($r = 0.19$, $p = 0.03$) (Table 4); indoor temperatures increased only 0.05°C for every 1°C increase outdoors. Building and neighborhood variables, on the other hand, were strongly associated with indoor temperature. The strongest predictor of indoor temperatures was the building type (AICc was over 30 points lower than the second-best univariate model); indoor temperatures in apartment buildings were approximately 2.5°C greater than in single and two family houses. The percent of rentals in a neighborhood and the floor of the dwelling were both positively and significantly associated with indoor temperatures; whereas the number of rooms in the study dwelling was negatively and significantly associated with indoor temperatures (Table 4).

The best multivariate model predicting indoor temperatures during the cool season included building type, outdoor temperature, and the percent of rentals in the neighborhood (Table 4). Indoor temperature increased 0.07°C for every 1°C increase outdoors and 0.02°C for every percent increase in neighborhood rentals. The number of rooms was inversely associated and the floor level of the dwelling was positively associated when added to a model with building type. All of the best multivariate models included building type, highlighting

Table 4. Coefficients (and 95% confidence intervals) for the five best multivariate linear models for indoor temperature (°C), while outdoor temperatures are less than 15°C. The coefficients for univariate models for each of the variables present in the multivariate models are included in the first column.

$n = 154$	Bivariate	Model 1	Model 2	Model 3	Model 4	Model 5
AICc	—	189.1	190.2	190.5	192.1	193.0
Outdoor temperature	0.05 (−0.01 0.12)	0.07 (0.02 0.11)	—	—	0.06 (0.01 0.11)	—
Building type	2.86* (2.26 3.46)	2.36* (1.63 3.09)	2.37* (1.64 3.11)	2.15* (1.40 2.90)	2.87* (2.28 3.45)	2.48* (1.81 3.16)
% of rentals in neighborhood	0.05* (0.03 0.06)	0.02 (0.02 0.03)	0.02 (0.02 0.03)	—	—	—
Outdoor specific humidity	0.06 (−0.00 0.13)	—	0.20 (0.03 0.35)	—	—	—
No. of rooms in household	−0.53** (−0.71 −0.34)	—	—	−0.22 (−0.39 −0.04)	—	−0.21 (−0.39 −0.03)
Floor of household	0.31* (0.20 0.42)	—	—	0.11 (0.00 0.22)	—	—

* $p = 0.0001$.
** $p = 0.01$.

the strength of its association to indoor temperatures in the cool season.

b. *Indoor specific humidity*

Mean indoor specific humidity was 9.7 g kg^{-1} across dwellings and ranged from 4.9–14.8 g kg^{-1} (Table 2). It is likely, however, that mean specific humidity was below 3 g kg^{-1} in several dwellings, but the data were excluded because the lower limit of the humidity sensor had been reached. Overall, the indoor environment has significantly less humidity content than the outdoor environment with indoor specific humidity approximately 2.5 g kg^{-1} less than outdoors on average (Wilcoxon signed rank test: $p < 0.0001$); however, indoor and outdoor specific humidity appeared to converge as humidity decreases. Indeed, indoor specific humidity may, in fact, be greater as outdoor specific humidity approached zero but the removed humidity observations limit the inference that can be made about low humidity conditions (Fig. 2).

Given the large number of humidity observations removed during dry conditions (Fig. 2), we limited our analysis to periods when specific humidity was greater than 10 g kg^{-1}. During these periods, indoor specific humidity was most strongly associated with outdoor specific humidity ($r = 0.60$, $p < 0.0001$) (Table 5), with indoor SH increasing 0.6 g kg^{-1} for every 1 g kg^{-1} increase in outdoor SH. Yet, it is interesting to note that the combination of outdoor temperature and relative humidity generates a better model—based on AICc, which penalizes models for an increased number of parameters—than specific humidity alone. The percent of housing rentals in the neighborhood and median household income were significant predictors of indoor specific humidity in a model that included outdoor specific humidity (or outdoor temperature and relative humidity) (Table 5). The percent of rentals was negatively associated with indoor specific humidity, whereas median household income was positively associated with indoor specific humidity. Further, several of the best-fitted multivariate regression models for indoor specific humidity include both outdoor temperature and specific humidity. The sign of the coefficient for outdoor temperature was negative when included with specific humidity in a regression model, whereas the coefficient was positive when temperature was alone or included in the same model with outdoor relative humidity (Table 5).

c. *Relative humidity*

The mean indoor relative humidity across study dwellings was 46.9%, with a range of 32.1%–66.2%. Again, the mean relative humidity in several dwellings was likely

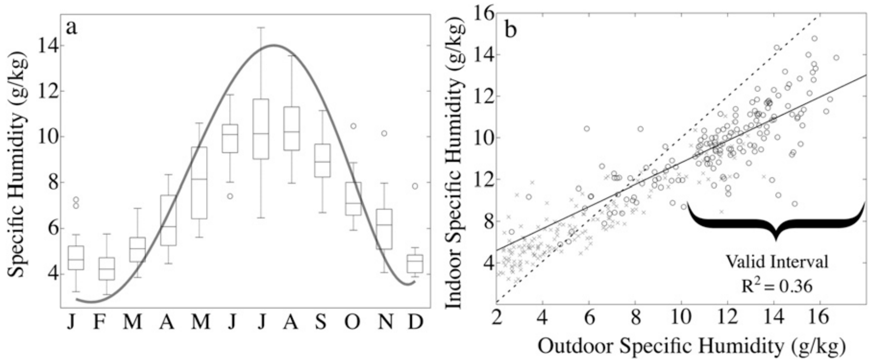

FIG. 2. (a) The seasonal variation of indoor (box plots) and outdoor (line plot) specific humidity by month. The seasonal plot shows the strong seasonal variability of specific humidity. (b) The relationship between indoor and outdoor specific humidity across households. The regression line was fit only for the valid data (circles). Because of a lower threshold of ~25% relative humidity for the humidity sensors, many household locations needed to be dropped (Xs); however, we calculated the specific humidity based on a relative humidity of 25%, thus, these values can be as interpreted as the maximum possible value of mean specific humidity for each household. The dotted line indicates the points at which indoor and outdoor specific humidity are equal. The "valid intervals" are the ranges of data that were used in the multivariate regression analysis.

significantly lower than the minimum values reported here, but these data were dropped. For the valid range of humidity data (i.e., specific humidity greater than 10 g kg^{-1}), outdoor relative humidity ($r = 0.48$, $p < 0.0001$) was clearly the strongest predictor of indoor relative humidity. However, the relationship between indoor and outdoor relative humidity shown here is misleading and would likely not exist if complete indoor humidity data were available. Indeed, a logistic regression model shows that outdoor RH has no association with whether indoor RH decreases to the lower operating threshold of the humidity sensors ($p = 0.99$; Fig. 3). Outdoor specific humidity, on the other hand, was a significant predictor of whether indoor RH decreases to the operating threshold of the humidity sensor in a household ($p < 0.0001$), with the probability increasing as specific humidity decreases (Fig. 4).

The best multivariate model for prediction of indoor relative humidity included outdoor relative humidity and temperature and neighborhood median household income. The model indicated a 1.79% point increase in relative humidity for every $10,000 increase in median neighborhood income. The percent of housing rentals in the neighborhood was also negatively associated with indoor RH when added to a model with outdoor temperature and RH, or outdoor RH and specific humidity (Table 6).

4. Discussion

The preceding analysis shows a number of interesting seasonal effects, especially with regard to indoor temperature. During the warm season (outdoor temperature greater than 15°C) outdoor temperature is the strongest predictor of indoor temperature. The relationship between outdoor and indoor temperatures during the warm season is very similar to those observed in other urban areas of North America such as Montreal, Canada (Smargiassi et al. 2008). The strong association between indoor and outdoor temperature during the warm season indicates that, in general, NYC households did not effectively mitigate the effects of hot outdoor temperatures. This is especially apparent when contrasted with the effectiveness of heating indoor air during the cool season. Increases in the number of rooms in a dwelling and the median household income in the neighborhood are negatively associated with indoor temperature in the warm season and may reflect greater air conditioner use in wealthier households and neighborhoods. Additionally, the use of modern and more efficient appliances that generate less heat may also be important. It should be noted, however, that although median household income and the number of rooms were significant predictors of household income ($p < 0.0001$) the strength of the association was only moderate ($r = 0.33$ and 0.34, respectively). We also found study households reporting water damage were significantly cooler. Water damage was included in the study because we thought it might be related to indoor humidity conditions. The relationship between water damage and cooler indoor summer temperatures may stem from greater air conditioner use, which can produce condensation and water damage if humid outdoor air enters a building and condenses on cooler surfaces (Brennan et al. 2002).

TABLE 5. Coefficients (and 95% confidence intervals) for the five best multivariate linear models for indoor specific humidity (g kg^{-1}), while outdoor specific humidity is greater than 10 g kg^{-1}. The coefficients for univariate models for each of the variables present in the multivariate models are included in the first column.

$n = 118$	Bivariate	Model 1	Model 2	Model 3	Model 4	Model 5
AICc	—	24.00	24.06	25.02	26.00	26.28
Constant	—	-17.0^{a} (-25.0 -14.1)	-6.4^{a} (-10.0 -2.9)	2.9^{b} (1.2 4.6)	-17.5^{a} (-22.8 -12.2)	-4.4^{b} (-7.8 -0.9)
Outdoor temperature	0.22^{a} (0.13 0.31)	0.56^{a} (0.46 0.66)	—	-0.40^{a} (-0.54 -0.24)	0.56^{a} (0.46 0.66)	-0.20 (-0.36 -0.04)
Outdoor relative humidity	0.03 (-0.02 0.07)	0.22^{a} (0.17 0.27)	0.09^{a} (0.6 0.13)	—	0.21^{a} (0.17 0.26)	—
Median household income in neighborhood (by $10,000)	0.14 (-0.06 0.34)	0.24^{a} (0.10 0.39)	0.24^{c} (0.10 0.39)	0.24^{c} (0.10 0.39)	—	—
Outdoor specific humidity	0.57^{a} (0.44 0.71)	—	0.70^{a} (0.58 0.82)	1.18^{a} (0.92 1.44)	—	0.70^{a} (0.57 0.82)
% of rentals in neighborhood	-0.67 (-1.80 0.46)	—	—	—	-0.01^{b} (-0.02 -0.00)	-0.01^{b} (-0.02 -0.00)

[a] $p = 0.0001$.
[b] $p = 0.01$.
[c] $p = 0.001$.

The wide range of indoor temperatures observed for similar outdoor temperatures during the warm season in NYC indicates that significant differences in thermal stress may exist for different subpopulations and households. For example, when outdoor temperatures averaged approximately 28°C, indoor temperature in some dwellings averaged greater than 30°C, while other dwellings averaged temperatures as low as 22°C (Fig. 1). Given that these values represent average temperatures over the course of several days, it is likely that some of these houses were substantially warmer at times. Such conditions are especially significant given that in ambient temperatures of 31°–33°C the body cannot lose heat from conductive and convective processes and must rely upon evaporative cooling, increasing the chances of hyperthermia (especially in humid conditions) and dehydration (Taylor 2006).

In contrast to the warm season, outdoor temperatures have a weak relationship with indoor temperatures during the cool season (mean outdoor temperatures below 15°C) in NYC. This is undoubtedly a reflection of the effectiveness of heating systems in apartment buildings and homes. Indeed, during the heating season in NYC landlords are required to sustain indoor temperatures of greater than 20°C when daytime temperatures decrease below approximately 13°C (http://www.nyc.gov/html/hpd/html/tenants/heat-and-hot-water.shtml). Mean indoor temperatures vary by more than 10°C in the cool season despite similar outdoor conditions (Fig. 1). In particular, apartment buildings are significantly warmer than one and two family homes. This difference likely represents different types of heating systems and levels of temperature control. For example, in NYC one and two family homes typically have forced-hot-air heating systems with thermostats that monitor indoor air temperature; whereas large apartment buildings typically use forced hot-water or steam-heating systems that are often controlled by outdoor air thermostats (Environmental Defense Fund 2009). Further, apartment dwellers often do not pay for heating, whereas those in single and two family houses often do. Indoor temperature during the cool season also increases as the floor of the dwelling increases. Because air density decreases as temperature increases, heated air may rise into higher floors and increase temperatures at these levels. This process may also draw cold outside air in laterally at lower floors, decreasing temperatures at these levels. There was no significant relationship between variables related to SES and indoor temperatures during the cool season. This is consistent with the finding of a previous study in the United Kingdom (Oreszczyn et al. 2006).

Although indoor specific humidity is strongly correlated with outdoor specific humidity—indicating

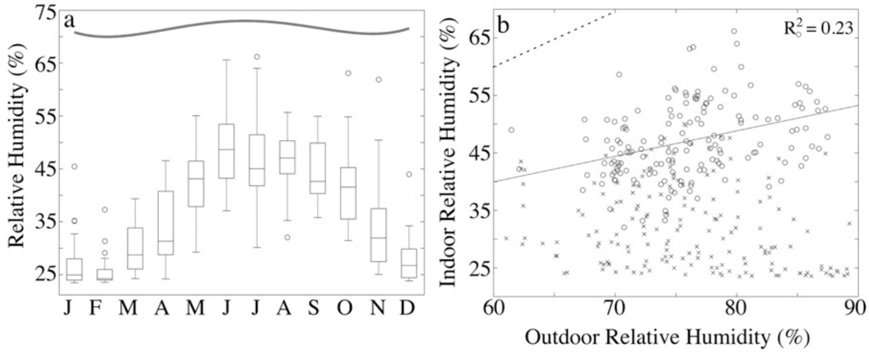

FIG. 3. (a) Indoor (box plots) and outdoor (line plot) relative humidity by month shows the strong seasonality of relative humidity indoors compared to the seasonal outdoor signal. (b) The relationship between indoor and outdoor relative humidity is shown at right. The regression line was only fit for the valid data (circles). Like specific humidity, many observations needed to be removed because of indoor relative humidity decreasing below the operating threshold of the humidity sensors at some point during monitoring.

significant air exchange between environments—indoor specific humidity is generally lower than outdoor specific humidity during months with high outdoor specific humidity (greater than 10 g kg^{-1}). It is unclear why indoor specific humidity is lower than outdoor humidity in these conditions given that numerous indoor activities generate water vapor such as cooking, bathing, and respiration. However, it is possible that this difference is a result of absorption of water vapor by indoor surfaces such as floors, furniture, and walls (Committee on Damp Indoor Spaces and Health 2004) and the removal of water vapor via air conditioning mechanisms. We also found that dwellings in wealthy neighborhoods had greater levels of specific humidity. This is surprising since it was hypothesized that air conditioning use, which can reduce the humidity content of the air, would increase with household wealth. It is possible that factors such as clothes and dish washing machines, and cooking behaviors eclipsed the drying effects of air conditioning. Also, as we mentioned previously, neighborhood income is not a strong predictor of household income so this association may be erroneous. We also found that outdoor temperature is inversely associated with indoor specific humidity when added to a model with outdoor specific humidity. This may indicate a greater reliance on air conditioning as temperatures increase, even as outdoor specific humidity remains relatively constant.

Indoor relative humidity was much lower than outdoor relative humidity and strongly seasonal with the lowest values in the winter and the highest values in the summer. The low levels of relative humidity in the winter are due to the heating of air indoors. During the summer, indoor relative humidity levels approach outdoor levels as indoor and outdoor temperature levels converge. The comparability between indoor and outdoor relative humidity may be enhanced by strong atmospheric mixing between indoor and outdoor spaces through open windows. We also deduced that outdoor relative humidity would not be a strong predictor of indoor relative humidity, particularly during the winter. This finding may be generalizable to all temperate regions that rely on heating indoor air during the winter and suggests that outdoor relative humidity conditions should not be used for correlation analyses in health

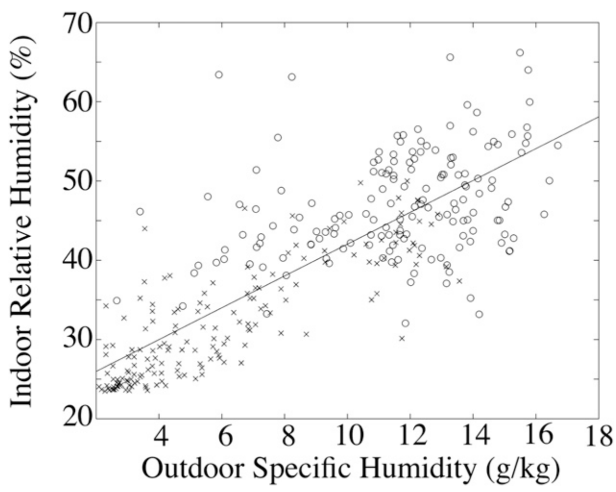

FIG. 4. The relationship between outdoor specific humidity and indoor relative humidity. The regression line was fit to both the valid and dropped data. Although there is uncertainty about the values of the dropped data points (Xs), we do know that their true values are lower than they are represented here; thus, the regression would likely become steeper and remain significant if complete relative humidity data were available.

TABLE 6. Coefficients (and 95% confidence intervals) for the five best multivariate linear models for indoor relative humidity (%), while outdoor specific humidity is greater than 10 g kg^{-1}. The coefficients for univariate models for each of the variables present in the multivariate models are included in the first column.

$n = 118$	Bivariate	Model 1	Model 2	Model 3	Model 4	Model 5
AICc	—	381.92	382.76	386.60	386.64	387.46
Constant	—	−50.0[a] (−71.7 −28.3)	−24.4[b] (−39.0 −9.7)	−33.8[b] (−55.3 −12.3)	42.1[a] (34.6 49.5)	−8.44 (−22.9 6.0)
Outdoor temperature	−0.17 (−0.24 0.58)	1.1[a] (0.70 1.50)	—	1.09[a] (0.68 1.49)	−2.80[a] (−3.46 −2.13)	—
Outdoor relative humidity	0.52[a] (0.35 0.69)	0.9[a] (0.71 1.09)	0.65[a] (0.50 0.80)	0.86[a] (0.66 1.05)	—	0.61[a] (0.46 0.76)
Median household income in neighborhood (by $10,000)	1.41[c] (1.23 1.60)	1.79[a] (1.18 2.40)	1.78[a] (1.18 2.40)	—	1.78[a] (1.16 2.41)	—
Outdoor specific humidity	0.69 (0.04 1.35)	—	1.38[a] (0.87 1.88)	—	4.89[a] (3.80 5.97)	1.35[a] (0.84 1.87)
% of rentals in neighborhood	−0.08[c] (−0.12 −0.04)	—	—	−0.09[a] (−0.12 −0.06)	—	−0.09[a] (−0.13 −0.06)

[a] $p = 0.0001$.
[b] $p = 0.001$.
[c] $p = 0.01$.

research where indoor conditions are important. On the other hand, we did find that outdoor specific humidity is a relatively strong predictor of indoor relative humidity (Fig. 4).

Several limitations to this study need to be addressed. One major limitation is that the humidity sensors employed could not measure relative humidity below ~25%. Thus, we were unable to generate a complete understanding of indoor humidity conditions, particularly during the winter when indoor RH values were extremely low. We also had only one datalogger per dwelling, although there could be substantial temperature and humidity variability within a single dwelling.

The temperature and humidity used here were measured as part of a study examining the environmental determinants of asthma and not specifically designed for the purpose of examining relationships between outdoor and indoor climate conditions. As such, some questions that would have proved informative for the purposes of this study—for example, heating and air conditioning system types and use patterns, exterior building material, solar radiation exposure, types of windows (e.g., insulated glazing), and quality of insulation and weatherization—were not available. We also had no information regarding the occupancy patterns of the residents in each household. It is possible that some dwellings were more consistently occupied and the environment was more managed than others. Thus, the differences in the measured variability of temperature and humidity are not necessarily representative of differences in exposures across households.

Another limitation of this study is that we did not have access to outdoor data at small scales across NYC. It is possible that meteorological variability within the city might have generated significant differences in indoor conditions. For example, temperatures can vary by 2°–4°C within urban areas due to differences in urban morphology and land cover (Lee et al. 2009; Zhang et al. 2011). It follows that future studies are needed to examine the potential effect of intra-urban spatial gradients of outdoor temperature and humidity on indoor conditions.

This study showed that the relationship between indoor and outdoor temperature and humidity conditions in NYC dwellings was associated with neighborhood level socioeconomic status indicators and certain building descriptors. Some of these factors may modify climate and weather-sensitive health risks within subpopulations of NYC, or in the city as a whole. Further study and characterization of indoor climatic variability is needed for a range of urban and nonurban environments. The results of such studies, as well as this study, may inform public health policy and future investigations of health outcomes for which temperature or humidity is an established risk factor. As understanding of the impact of indoor environmental conditions on human health improves, such insight may motivate more effective management of indoor environments and improve public health.

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