International Journal of Biometeorology (2021) 65:479–488
https://doi.org/10.1007/s00484-020-02036-2

ORIGINAL PAPER

Indoor heat exposure in Baltimore: does outdoor temperature matter?

D. W. Waugh[1] · Z. He[1] · B. Zaitchik[1] · R. D. Peng[2] · G. B. Diette[3] · N. N. Hansel[3] · E. C. Matsui[3] · P. N. Breysse[4] · D. H. Breysse[4] · K. Koehler[4] · D. Williams[4] · M. C. McCormack[3,4]

Received: 14 March 2020 / Revised: 6 October 2020 / Accepted: 14 October 2020 / Published online: 21 October 2020

Abstract

Heat exposure of a population is often estimated by applying temperatures from outdoor monitoring stations. However, this can lead to exposure misclassification if residents do not live close to the monitoring station and temperature varies over small spatial scales due to land use/built environment variability, or if residents generally spend more time indoors than outdoors. Here, we compare summertime temperatures measured inside 145 homes in low-income households in Baltimore city with temperatures from the National Weather Service weather station in Baltimore. There is a large variation in indoor temperatures, with daily-mean indoor temperatures varying from 10 °C lower to 10 °C higher than outdoor temperatures. Furthermore, there is only a weak association between the indoor and outdoor temperatures across all houses, indicating that the outdoor temperature is not a good predictor of the indoor temperature for the residences sampled. It is shown that much of the variation is due to differences in the availability of air conditioning (AC). Houses with central AC are generally cooler than outdoors (median difference of − 3.4 °C) while those with no AC are generally warmer (median difference of 1.4 °C). For the collection of houses with central or room AC, there is essentially no relationship between indoor and outdoor temperatures, but for the subset of houses with no AC, there is a weak relationship (correlation coefficient of 0.36). The results presented here suggest future epidemiological studies of indoor exposure to heat would benefit from information on the availability of AC within the population.

Keywords Indoor temperature · Outdoor temperature · Housing · Air conditioning · Heat exposure

Introduction

Heat exposure of a population is often estimated by applying temperatures from outdoor, central site monitoring stations. However, this can lead to exposure misclassification as most residents do not live close to the monitoring station, and heat exposure can vary at the neighborhood scale (Basu 2009) Furthermore, and arguably more importantly, individuals in industrialized countries spend 90% or more of their time indoors (Hoppe and Martinac 1998; Klepeis et al. 2001), and indoor temperatures are likely to better represent personal heat exposure (White-Newsome et al. 2012; Smargiassi et al. 2008). However, at present, the association between indoor conditions and the observations from a central weather monitoring, and the heterogeneity of among different indoor environments, is poorly known. While the association between outdoor temperature measurements and population health may be relevant from an epidemiologic perspective, understanding the relationship between indoor and outdoor temperature may be more relevant to developing interventions for mitigating heat exposure at the individual level.

As understanding health effects of climate change is increasingly recognized as a research and public health priority (IPCC 2018; USGCRP 2018; Watts et al. 2018), recognizing and addressing limitations of the methodology for exposure

P.N. Breysse is currently employed by the Centers for Disease Control and Prevention, and is serving in his personal capacity.

✉ D. W. Waugh
waugh@jhu.edu

[1] Department of Earth and Planetary Sciences, Johns Hopkins University School of Arts and Sciences, Baltimore, MD, USA

[2] Department of Biostatistics, Johns Hopkins University School of Public Health, Baltimore, MD, USA

[3] Department of Medicine, Johns Hopkins University School of Medicine, Baltimore, MD, USA

[4] Department of Environmental Health Sciences, Johns Hopkins University School of Public Health, Baltimore, MD, USA

assessment is imperative. Heat exposure has been linked with increases in mortality through studies of extreme heat events (e.g., Kaiser et al. 2001; Naughton et al. 2002), and through time series analyses of large population datasets (Basu 2009). Heat exposure has also been associated with increases in cardiopulmonary morbidity (Anderson et al. 2013), asthma exacerbations (Lin et al. 2009), and COPD (McCormack et al. 2016). Individuals that are from low-income households and minorities living in urban areas have been identified as susceptible to the adverse effects of heat due to poor access to air conditioning and healthcare (Harlen et al. 2006; Madrigano et al. 2015). However, very few studies include individual level exposure assessment such as indoor or personal assessment of heat exposure.

Only a limited number of studies have examined the relationships between indoor and outdoor temperatures in residential dwellings within the USA. Tamerius et al. (2013) and Quinn et al. (2014) analyzed data from two separate large-cohort studies in New York City, where indoor temperature measurements were made in a large number of houses (327 and 285, respectively) for 1–2-week periods spread over multiple years; Quinn et al. (2017) analyzed data from 36 apartments in New York City during two summers; and White-Newsome et al. (2012); Nguyen et al. (2014), and Vant-Hull et al. (2018) analyzed measurements made in a similar number of houses (30 in Detroit, 16 in Boston, and 30 in New York City respectively) for a single summer/year. In addition, Nguyen and Dockery (2016) examined the indoor-outdoor temperature relationships for houses in eight locations across the northern hemisphere. All these studies found some association between the indoor temperatures and those from an outdoor monitoring station, but the strength of this association and the sensitivity of indoor to outdoor temperatures varied, and there remain large uncertainties in the indoor to outdoor temperature relationship.

Here we examine the indoor to outdoor temperature relationship using temperature measured inside homes of a large-cohort study of children with asthma in low-income households living in Baltimore City. The variability of the temperatures of the homes of this vulnerable population, and its association with outdoor conditions, has not previously been quantified and is valuable information for future epidemiological studies of this population. Furthermore, the previous large-cohort studies discussed above (Tamerius et al. 2013; Quinn et al. 2014) consider a different city (New York City), populations, and housing characteristics, and comparisons with these studies provide useful information of how indoor-outdoor relationship varies between cities and populations.

As well as quantifying the variability across the study population we also examine the impact air conditioning (AC) plays on this variability and indoor-outdoor relationships. The use of AC is expected to have an impact on indoor temperatures and the relationship with outdoor conditions, but few studies have quantified this impact. Information on AC usage was not available for the Tamerius et al. (2013) and Quinn et al. (2014) large-cohort studies, and there is AC information only in studies involving a small number of houses (Nguyen et al. 2014, White-Newsome et al. 2012; Quinn et al. 2017; Vant-Hull et al. 2018). Furthermore, these studies only reported limited information on the impact of AC. Exceptions include White-Newsome et al. (2012) who report a higher sensitivity of indoor temperatures to outdoor temperature for houses without AC compared to those with AC, and Quinn et al. (2017) who found lower indoor temperatures for homes with central AC than homes with room ACs, and a very weak association between indoor and outdoor temperatures for homes with AC. However, as these studies used a small number of homes with different locations and characteristics, it is not known how the availability of AC will impact temperatures for the population considered here. Therefore, we examine the impact of AC on indoor temperatures, and the role this plays in the variability among homes and the association between indoor and outdoor temperatures.

Data and methods

Study design

The residences monitored in this study are from two US *National Institute of Environmental Health Sciences* (NIEHS)-funded cohort studies (DISCOVER and Asthma-Diet) investigating the effect of indoor environmental exposures on childhood asthma. Although the focus of these studies is not the difference between indoor and outdoor climates, the data collected can be used to examine this issue. Children ages 5–12 living in Baltimore City were enrolled in these studies. The social economic conditions of the areas containing the vast majority of the houses are similar, i.e., the vast majority of the houses are located in ZIP codes where the median house incomes are between USD 20,000 and USD 30,000, the percentage vacant houses are between 15 and 25%, and there is a majority African-American population.

A house survey that included information on the residence type (e.g., row-home, apartment, or single-family house), distance from street, and type of cooling system (central air conditioning, window air conditioned in specific rooms) was completed by a field worker before each visit. The sampled residences were mostly (78%) "row homes" (a row of houses that share walls, and sometimes referred to as terraced or town houses), while there was a roughly equal split between houses with central air conditioning, room air conditioning, and no air conditioning, see Table 1.

Each participant underwent 1 week of home environmental monitoring in each of four consecutive seasons for a total of 4 weeks of monitoring (i.e., 4-week-long monitoring periods

Table 1 Housing characteristics. A house is classified as room AC only if AC unit is in the room where the T measurements were made

Housing characteristics	N = 145 homes
Air conditioning	Central (36%), room (26%), none (38%)
House type	Row House (78%), Apartment (13%), other (9%)
Room sampled	Bedroom (86%), Family Room (6%), Living Room (4%), Kitchen (4%)
No. of floors in building (mean, SD)	2.1 (0.4) min = 1, max = 4
Presence of basement (%)	76.2%

each separated by 3 months). Here we consider only summer (June to August) measurements as extreme heat and heat exposure are most common in this season. During summers between 2009 and 2013, week-long visits were made to 145 homes.

Measurements

Temperature and humidity were measured inside the participant's homes using HOBO (Onset, Inc. Poccasette, MA) H08-007 temperature and humidity data loggers. The data loggers record temperature with accuracy around 0.7 °C and relative humidity with accuracy of ± 5%. In most cases, the data loggers were placed in the child's bedroom (86%), see Table 1. Measurements were recorded at 5-min intervals, from which we calculated hourly averages. All analysis was performed on these hourly average temperatures.

The majority of the houses sampled are located in inner Baltimore City. The mean distance of the houses from the National Weather Service (NWS) automated observing station located in the Baltimore Inner Harbor is 5.2 km, with minimum of 0.7 km and maximum of 14.4 km, see Fig. 1.

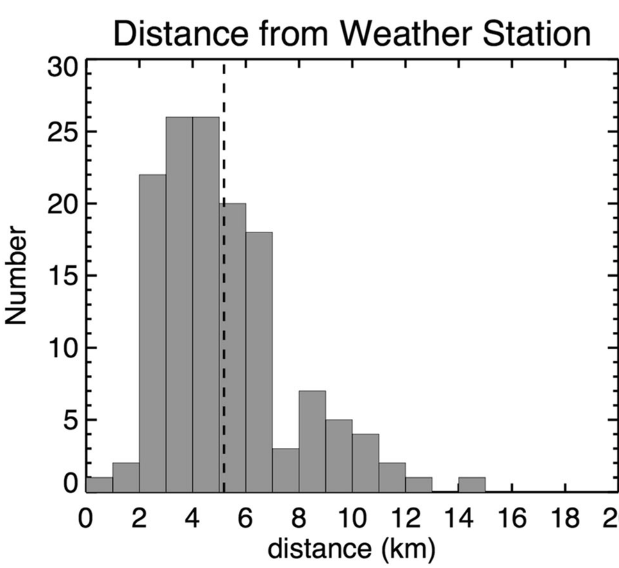

Fig. 1 Histogram of the distance of houses from the NWS weather station in Baltimore city. Vertical dashed line shows the mean distance

Hourly temperature and humidity measurements were made at the NWS station, and we refer to these station data as "outdoor" data. These data are available for each day during the summers between 2009 and 2013, but indoor measurements are not made on each day. We include here only outdoor measurements for times when there is also an indoor measurement. Specifically, each hourly measurement inside a house is matched with measurements made at the weather station at the same time. If measurements were made in two houses at the same time, then the outdoor data is duplicated for that time. This means that we have exactly the same number of indoor and outdoor temperatures, with each made at the same time.

Analysis

We examine the variability and relationships between the indoor temperature (T_{in}), outdoor temperature (T_{out}), and the difference between these two measurements ($\Delta T = T_{in} - T_{out}$) for (i) hourly data, (ii) daily statistics (daily minimum, mean, and maximum hourly values), and (iii) mean and variance of hourly data for each 6–8-day visit to a home (referred to as an "individual house visits," with mean over this visit being referred to as the "visit mean").

We use the Pearson product-moment correlation coefficient (r) and the slope β of the ordinary least squares regression to quantify the relationships between indoor and outdoor measurements. The correlation coefficient is a parametric test that measures the degree of linear correlation between the indoor and outdoor measurements, while the linear regression coefficient β is an estimate to the change in indoor value for unit change in outdoor value, i.e., for regression between indoor and outdoor temperature, $T_{in} = \alpha + \beta T_{out}$, β is the change in T_{in} for a 1-degree increase in T_{out}. The Student t test is used to test if there is a difference in the mean temperature between housing with different AC types.

Our main focus is on temperature variations, but as there is also interest in variations of humidity and heat indices, we have also performed the above analysis on the relative humidity (RH), dew point (T_d), and heat index (HI). The dew point is calculated using Eq. (8) of Lawrence (2005) and heat index using formula in Rothfusz (1990).

Results

Temperature and humidity measurements

To quantify the variability across all houses, we compare the diurnal cycle of all indoor and outdoor measurements. The measured T_{out} has a large diurnal cycle, with an average daily maximum value around 30 °C (occurring in late afternoon, 2–3 pm) and an average minimum value around 24 °C (occurring in early morning, 5–6 am) (see Fig. 2). There is however large variability between days (due to variability in meteorological conditions), with the daily maximum varying between 21 and 41 °C. T_{in} also has a diurnal cycle, but with a much weaker amplitude than outdoors (~ 2 °C compared to ~ 7 °C), due to both cooler afternoons and warmer overnight indoor compared to outdoors. There is also a difference in timing of maximum temperatures, with the maximum T_{in} occurring around 2 h later than T_{out}. A smaller diurnal variation indoors and lag of 2–3 h were also found by earlier studies (Quinn et al. 2014; Vant-Hull et al. 2018).

These differences between indoor and outdoor temperatures are quantified in Fig. 3, which shows the histograms of ΔT for the daily mean, minimum, or maximum temperature. (The daily minimum and maximum temperatures occur in the early morning (around 6 am) and mid-afternoon (around

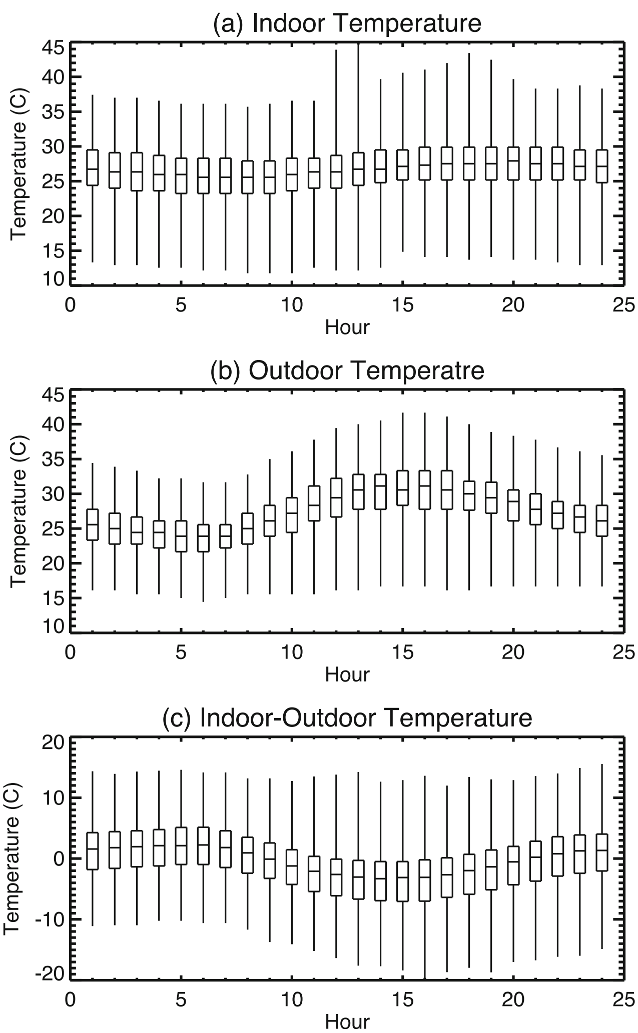

Fig. 2 Box-whisker plots for hourly data, for all data for June–August, 2009–2013. The box shows the lower and upper quartile, and whiskers show maximum and minimum values

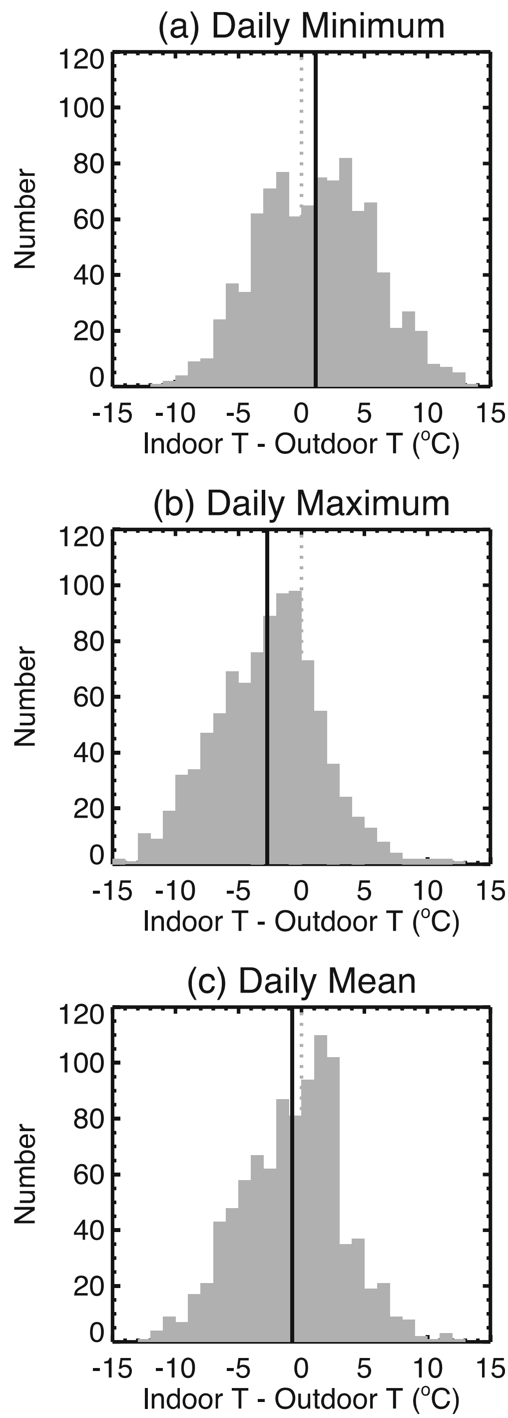

Fig. 3 Histogram of indoor-outdoor differences in daily minimum (**a**), maximum (**b**), and mean temperatures (**c**), for all hourly data for June–August, 2009–2013. Vertical solid line is the mean value

3 pm), and the distributions of temperature difference ΔT at 6 am and 3 pm are very similar to distributions of ΔT for daily minimum and daily maximum temperature, respectively.) The most striking feature is the very wide spread in ΔT, with values ranging from less than − 10 °C to greater than 10 °C. This means that within the study populations, there are residences/days where indoors are much colder than outdoors while for other residences/days, the reverse holds. The large variability in ΔT occurs for all three metrics and hence occurs at day and night. There is, however, some diurnal variation in ΔT, with the indoor daily minimum (early morning temperatures) slightly warmer on average than outside ($\Delta T \sim 1$ °C) while the indoor daily maximum (afternoon temperatures) cooler on average by around 5 °C. The larger differences during the day than at night result in the daily mean T_{in} being lower on average than T_{out} by around 2.5 °C (see Fig. 2).

Analysis of relative humidity (RH), dew point (T_d), and heat index (HI) shows qualitatively similar results, with a broad distribution of indoor-outdoor differences and diurnal variations in the mean indoor-outdoor differences, see Fig. 4. The population-mean daily minimum RH is close to zero (with differences generally between − 20 and + 20%), but population-mean indoor daily maximum RH is around 20% less than outdoors (with indoor values less than outdoor for nearly all measurements). The population-mean difference in dew point shows a much smaller diurnal variations, with the mean indoor dew point around 5 °C less than outdoors for daily minimum, maximum, and mean values.

The large variability in ΔT could be due to different meteorological conditions and changes in T_{out}. However, there is only a weak association between indoor and outdoor temperatures (Table 2). For example, the correlation coefficient between daily maximum T_{in} and T_{out} is $r = 0.22$ and the regression coefficient $\beta = 0.23$, i.e., variations in T_{out} explain only $R^2 = 0.05$ of the variance in T_{in}, and on average, there is only a 0.23 °C increase in the daily maximum T_{in} for a 1 °C increase in daily maximum T_{out}. This low correlation indicates that the outdoor temperature is not a good predictor of the indoor temperature for the residences sampled.

Impact of air conditioning

As T_{out} is not a good predictor, other factors must play an important role in determining T_{in}. While other meteorological factors (solar radiation, wind) could be playing a role, analysis of the indoor-outdoor temperature differences for houses sampled at the same time indicates that differences between houses, and not meteorology, are the major cause of the variability in ΔT. Furthermore, this analysis suggests that the availability of air conditioning (AC) is key factor for differences between houses.

The role of AC is illustrated in Fig. 5a, where the T_{in} are shown from three houses that were all sampled from late May to early June 2010. These houses are all row homes but they differ in the availability of AC, and there is corresponding differences in T_{in} between houses (even though they were sampled over the same period). One house (H-central) has central air conditioning and there are only small diurnal or day-to-day variations T_{in} in this house for the 7 days sampled, and T_{in} is nearly always less than the T_{out} (with small differences at night but large differences during the day). This is consistent with a house with effective cooling. In contrast, house H-no has no air conditioning and T_{in} in this house is between 32 and 36 °C (mean of 34.0 °C) and is always larger than T_{out} (with large differences at night). Consistent with a house with no cooling system and very limited ventilation, the third house (H-room) has room AC in the room where measurements were made, and for this house, T_{in} and T_{out} are comparable, both in terms of mean values and variability, although the indoor variability is less than outdoors.

There is also a difference in the indoor humidity between these three houses, as illustrated in Fig. 5b which shows the dew point temperature for the three houses and the outdoor station. Consistent with population-mean difference in dew point (Fig. 4), the indoor dew point is nearly always less than that outdoors. The largest difference (of up to 10 °C) occurs for the house with central AC. This is likely due to removal of water vapor by the air conditioning.

The three examples shown in Fig. 5 are representative of variability across houses, and there are many houses where both the mean and standard deviation of T_{in} are much less than outdoors (i.e., T_{in} varies little during the visit and is nearly always less than T_{out}, e.g., H-central) as well as many houses where visit mean of T_{in} are much greater than outdoors but indoor standard deviation is still smaller (i.e., T_{in} varies little but is nearly always greater than T_{out}, e.g., H-no). This suggests that the availability of AC drives much of the variability in ΔT.

To test this hypothesis, we separate the houses into those with central, room, or no AC, and examine the distribution of ΔT for each class. In this analysis, we consider a house to have room AC if there is no central air conditioning but there is an AC unit in the room where the T measurements were made. If there is an AC unit in another room, then the house is classified as no AC.

As might be expected, consideration of the availability of AC alters the relationship between indoor and outdoor temperatures. When all houses are included, there is essentially no relationship between the mean T_{in} and T_{out} for each 6–8-day visit to a house ($r = 0.04$, Table 3). Similarly, there is very weak association ($r \leq 0.05$) for the subset of houses with central or room AC (Table 3, Fig. 6a, c). When the subset of houses with no AC are considered, there is a weak relationship between T_{in} and T_{out} ($r = 0.36$), with $\beta = 0.56$, i.e., an average increase of 0.56 °C in T_{in} for a 1 °C increase in T_{out} (Fig. 6e).

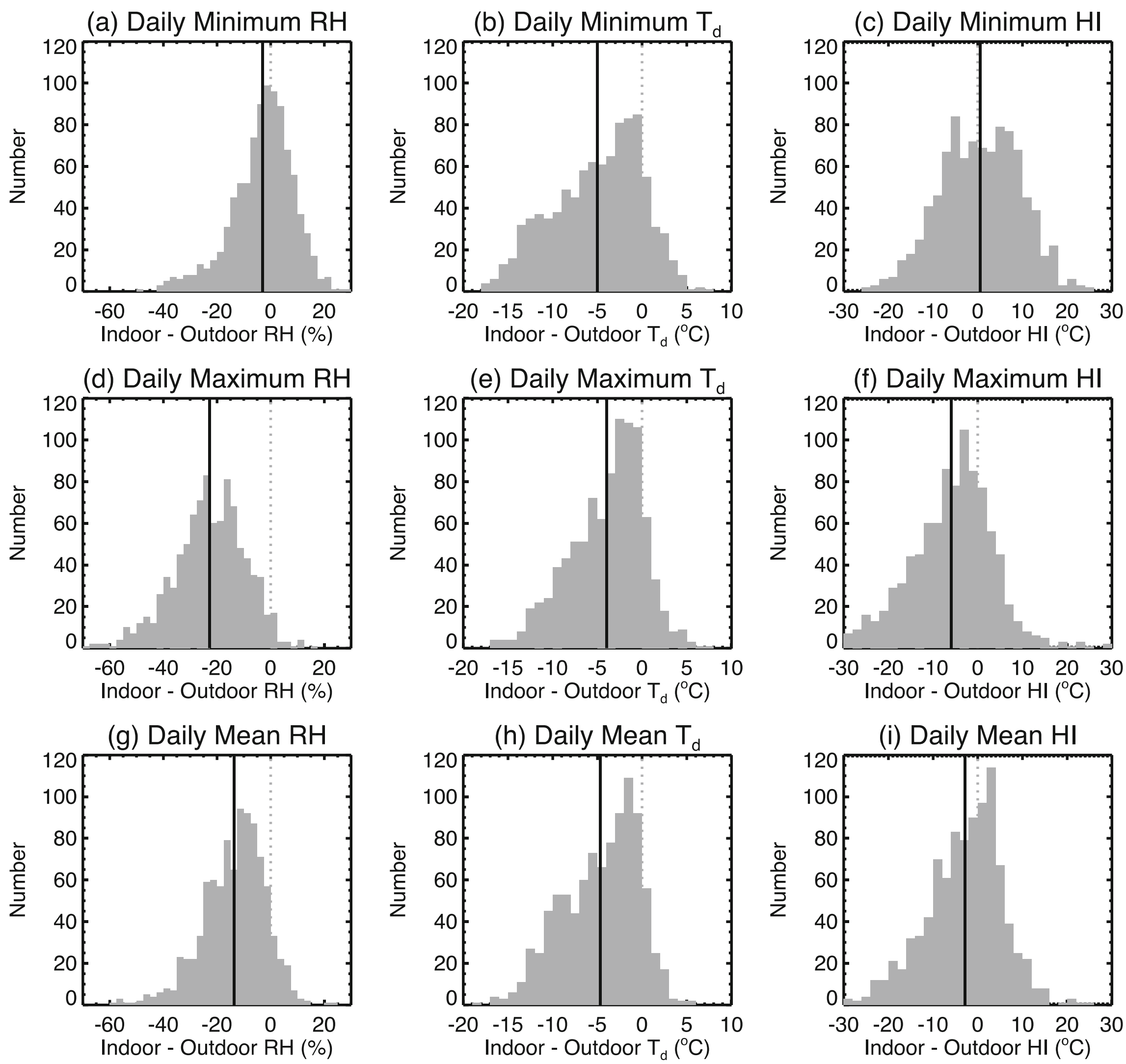

Fig. 4 **a**–**i** Histogram of indoor-outdoor differences in daily minimum, maximum, and mean (left) relative humidity, (middle) dew point, and (right) Heat Index, for all hourly data for June–August, 2009–2013. Vertical solid line is the mean value

There are also differences in the distribution of mean ΔT for each visit to a house between the three AC categories, with ΔT generally negative for houses with central AC and generally positive for houses with no AC, see Fig. 6, Table 3. The median value of ΔT for houses with central AC is negative (− 3.4 °C), while the median value is just less than zero (− 0.15 °C) for houses with room AC and positive (1.4) for houses with no AC. A similar variation is found for the mean value, see Table 3. Application of the *t* test shows that the difference between mean values for the central AC and no AC subsets is statistically significant at $p \sim 10^{-6}$, while the differences between room AC and no AC are significant at $p = 0.04$. These data show that availability of AC is likely a major factor in determining $T_{in.}$

Table 2 Pearson correlation coefficient r, and intercept α, and regression coefficient β for ordinary least squares regression between daily minimum, mean, and maximum indoor and outdoor T

	Daily minimum	Daily mean	Daily maximum
Correlation r	0.16	0.19	0.22
Intercept α	18.74	20.27	24.71
Regression β	0.24	0.23	0.23

Discussion

While the use of air conditioning explains much of the variability between indoor temperatures of houses, there is still a spread in ΔT for houses with same availability of air conditioning, and there is not complete separation between the ΔT distributions for the three categories (Fig. 6). There are several possible reasons for the overlap. First, we have information only on existence of air conditioning and not whether the AC

Fig. 5 Illustrations of temporal variation of indoor temperature (**a**) and dew point temperature (**b**) for three houses with different AC availability (H-central, blue; H-room, black; H = no, red) and the NWS weather station (cyan) for the end of May to early June 2010

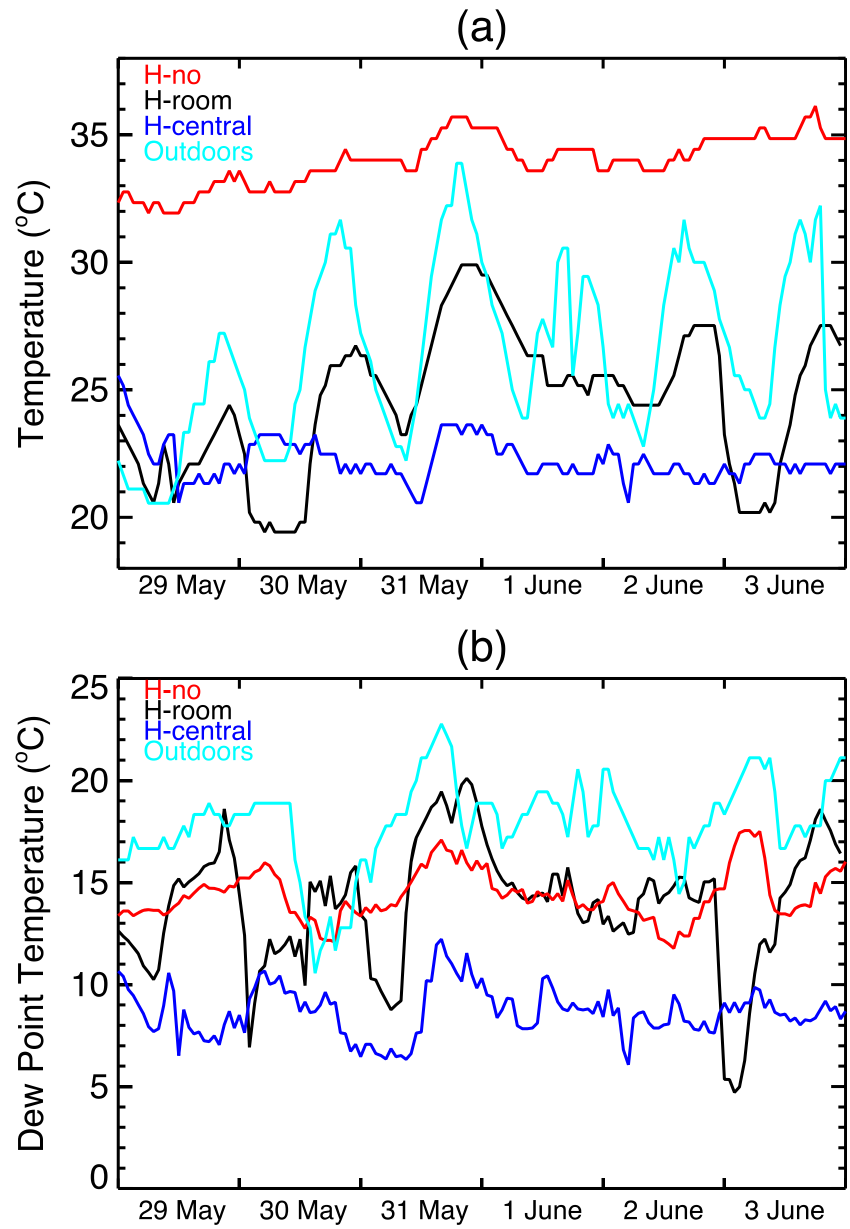

Table 3 Statistics of indoor-outdoor difference ΔT (median, mean, and standard deviation) and linear relationships between indoor and outdoor temperature for the mean temperature for each visit to a house. Statistics are for all houses and for subsets of houses classified by availability of air conditioning. Room AC means AC unit in room with T measurements. AC information is not available for 5 houses

	All $N = 145$	Central AC $N = 50$	Room AC $N = 37$	No AC $N = 53$
Median	0.01	− 3.4	− 0.15	1.4
Mean	− 0.4	− 2.1	− 0.3	1.1
Stand. Dev.	3.6	3.8	3.4	2.8
Correlation r	0.04	− 0.07	− 0.09	0.36
Intercept α	25.2	27.9	30.0	12.9
Regression β	0.06	− 0.10	− 0.11	0.56

was used. This likely explains the cases where $\Delta T > 0$ °C for houses with central or room AC. (Visual inspection of the cases with large ΔT shows diurnal variations in T_{in}, supporting this hypothesis.) Another possible reason is incorrect survey/housing information. For example, a few houses that are classified as having no central or room AC had relatively constant temperatures less than 24 °C throughout the visit ($\Delta T < 0$ °C), which suggests that there was some air conditioning. This could have been due to a room air conditioner that was moved into the room during a study period but not present at the time of home inspection. While it may be possible to reclassify some of the houses based on inspection of the temperature, this would be subjective and would introduce additional errors in the analysis.

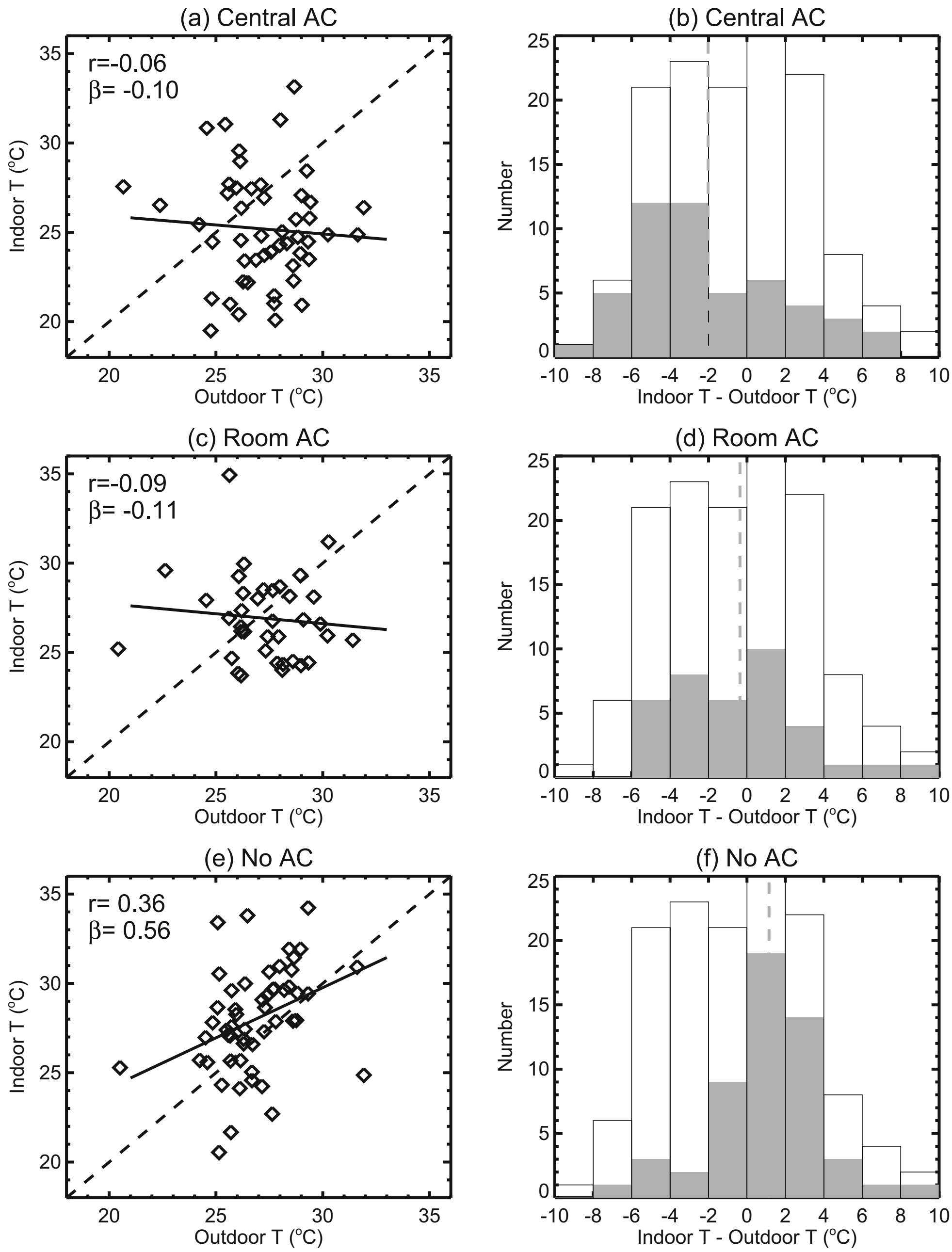

Fig. 6 Indoor and outdoor mean temperature for each visit to a house, for houses with central AC (**a**, **b**), room AC (**c**, **d**), or no AC (**e**, **f**). The left column shows the relationship between indoor and outdoor T, while the right column shows histograms of indoor-outdoor difference (with the mean difference shown by the vertical dashed line). The filled histograms on the right side show the distribution for each type of AC use, while the unfilled histogram is the same in each panel and shows the distribution for all houses (the value for 0–2 °C is 37, and is off the scale)

It is also possible that other characteristics are causing variability in ΔT. Possibilities include the use (e.g., bedroom or family room), the type of house, the floor sampled, window direction, use of shades, or shading by trees. Information on the room sampled and house type are available (Table 1), but unfortunately we do not have information on the other aspects. The vast majority of measurements considered were made in the bedroom (86%) of row houses (74%) so we cannot robustly assess the impact of the use of the room sampled or house type on ΔT. However, if only measurements from bedrooms or measurements in row houses are considered, there is still a broad distribution of the mean T_{in} for each visit, indicating that room or house type is not the cause of the wide range of T_{in} shown above.

There is some spread in the locations of houses sampled (Fig. 1), and variations in the outside temperature among house locations could be contributing to some of the variation. However, analysis of T_{in}, for all houses or just for houses with no AC, shows very weak relationship with location within the city (e.g., correlation coefficient of ΔT with distance from the weather station equals -0.1 for houses with no AC). In addition, analysis of outdoor measurements made in different locations within Baltimore City shows spatial variance which is much smaller than the house-to-house variability in ΔT found here (e.g., Scott et al. (2017) report a standard deviation of 1 °C for daily minimum temperatures for houses in east Baltimore, and later measurements with wider coverage show only a slightly larger standard deviation of 1.2 °C).

Our results differ from previous studies (White-Newsome et al. 2012; Tamerius et al. 2013; Quinn et al. 2014, 2017) that have reported stronger associations between indoor and outdoor temperatures for residential dwellings within other US cities (correlation coefficient r varying between 0.6 and 0.91). The cause for these differences is not known and could be due to a range of factors, including differences between seasons, cities, housing characteristics, urban environment, occupants, and use of AC. Given that we have shown large differences between homes with differing AC, the use of AC in the populations in other studies could be an important difference. Unfortunately, Tamerius et al. (2013) and Quinn et al. (2014) did not have information on availability of air conditioning within the study houses, and we cannot assess if differences in prevalence of AC could explain the different associations between indoor and outdoor temperatures. However, our results are qualitatively consistent with White-Newsome et al. (2012), who report a higher regression coefficient to outdoor temperature for houses without AC compared to those with AC, and Quinn et al. (2017), who found lower indoor temperatures for homes with central AC than homes with room ACs and a very weak association between indoor and outdoor temperatures for homes with AC.

Prior studies have suggested that the associations between heat exposure and health consequences differ by individual characteristics and home characteristics, including likely access to air conditioning (O'Neill et al. 2003; Medina-Ramon et al. 2006; Schwartz 2005). The results presented here demonstrate limitations of epidemiology studies that use data from central site monitoring stations to estimate the heat exposure of a population, if the population spend a large percentage of their time indoors. Our results suggest that if there is no air conditioning, then there is a weak association between indoor T and monitoring station T. However, if there is air conditioning use, which can be the case even for a low-income population in inner city (as considered here), then there will likely be limited connections between indoor T (and individual heat exposure) and temperature from a central (or any) monitoring stations.

It is also important to note that for houses with no air conditioning, the indoor temperature is generally warmer than the monitoring station (with large differences at night). This means that people who stay at indoors (e.g., elderly, asthma-prone children) in these houses are experiencing larger nighttime heat exposure than if outdoors, an exaggeration of the urban heat island effect in which urban areas do not experience nighttime cooling due to heat retained by dark roofs and concrete surfaces. Prior studies have suggested that disparities in heat-related health effects are partially attributable to access to central air conditioning which contributes to some of the differences in heat effects by race (O'Neill et al. 2005). The current study in a population of predominantly African American children from low-income households in Baltimore City quantifies the influence of air conditioning on indoor temperature during summer months and demonstrates that the strongest influence on cooler indoor temperatures was the presence of central air conditioning. These findings support the recommendation that efforts to reduce adverse health effects of heat exposure should consider access to air conditioning.

Conclusions

Analysis of temperature measurements made within homes in Baltimore City has shown that there is a large range in the difference between indoor temperature (T_{in}) and that at the central monitoring station (T_{out}), with indoor-outdoor temperature differences (ΔT) in daily minimum or daily maximum temperatures varying from less than − 10 °C to greater than 10 °C. Furthermore, there is only a weak association between the indoor and outdoor temperatures when all houses are included, suggesting that monitoring station temperature is not a good predictor and other factors play a more important role in determining indoor heat.

Much of the variation in differences between ambient temperature and indoor temperature was due to temperature differences between houses. In turn, a major cause of this variability is the availability of air conditioning. Houses with central air conditioning were generally cooler than outdoor (median $\Delta T = -3.4$ °C), while those with no air conditioning were generally warmer (median $\Delta T = 1.4$ °C). Furthermore, for the collection of houses with central or room AC, there was essentially no relationship between indoor and outdoor temperatures, but for the subset of houses with no AC, there is a weak relationship (variations in outdoor T explain 11% of variance of indoor T).

The above indicates that information on the percentage of households with AC within a population is needed for epidemiology studies of heat exposure and for the development of heat-wave response strategies. The measurement error in these studies would likely also be improved with individual-level monitoring, although this may not always be feasible.

Funding This work was supported by funding from a JHU Environment, Energy, Sustainability and Health Institute seed grant, NIEHS grants R21ES024021 and P01ES018176, NIEHS and EPA grant P50ES015903, and EPA grant 83451001.

References

Anderson GB, Dominici F, Wang Y, McCormack MC, Bell ML, Peng RD (2013) Heat-related emergency hospitalizations for respiratory diseases in the Medicare population. Am J Respir Crit Care Med 187:1098–1103

Basu R (2009) High ambient temperature and mortality: a review of epidemiologic studies from 2001 to 2008. Environ Health 8:40

Harlan SL, Brazel AJ, Prashad L, Stefanov WL, Larsen L (2006) Neighborhood microclimates and vulnerability to heat stress. Soc Sci Med 63:2847–2863

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

Intergovernmental Panel on Climate Change (2018) IPCC special report on the impacts of global warming of 1.5 °C: summary for policy makers. Incheon, Korea. https://www.ipcc.ch/sr15/. Accessed 28 Jan 2019

Kaiser R, Rubin CH, Henderson AK, Wolfe MI, Kieszak S, Parrott CL, Adcock M (2001) Heat-related death and mental illness during the 1999 Cincinnati heat wave. Am J Forensic Med Pathol 22:303–307

Klepeis NE et al (2001) The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants. J Expo Anal Environ Epidemiol 11:231–252

Lawrence MG (2005) The relationship between relative humidity and the dewpoint temperature in moist air: a simple conversion and applications. Bull Am Meteorol Soc 86:225–233

Lin S, Luo M, Walker RJ, Liu X, Hwang SA, Chinery R (2009) Extreme high temperatures and hospital admissions for respiratory and cardiovascular diseases. Epidemiology 20:738–746

Madrigano J, Ito K, Johnson S, Kinney PL, Matte T (2015) A case-only study of vulnerability to heat wave–related mortality in New York City (2000–2011). Environ Health Perspect 123:672–678

McCormack MC, Belli AJ, Waugh D, Matsui EC, Peng RD, Williams DA et al (2016) Respiratory effects of indoor heat and the interaction with air pollution in COPD. Ann Am Thorac Soc 13:2125–2131

Medina-Ramon M, Zanobetti A, Cavanagh DP, Schwartz J (2006) Extreme temperatures and mortality: assessing effect modification by personal characteristics and specific cause of death in a multi-city case-only analysis. Environ Health Perspect 114:1331–1336

Naughton MP, Henderson A, Mirabelli MC, Kaiser R, Wilhelm JL, Kieszak SM, Rubin CH, McGeehin MA (2002) Heat-related mortality during a 1999 heat wave in Chicago. Am J PrevMed 22:221–227

Nguyen JL, Dockery DW (2016) Daily indoor-to-outdoor temperature and humidity relationships: a sample across seasons and diverse climatic regions. Int J Biometeorol 60:221–229

Nguyen JL, Schwartz J, Dockery DW (2014) The relationship between indoor and outdoor temperature, apparent temperature, relative humidity, and absolute humidity. Indoor Air 24:103–112

O'Neill MS, Zanobetti A, Schwartz J (2003) Modifiers of the temperature and mortality association in seven US cities. Am J Epidemiol 157:1074–1082

O'Neill MS, Zanobetti A, Schwartz J (2005) Disparities by race in heat-related mortality in four US cities: the role of air conditioning prevalence. J Urban Heal 82:191–197

Quinn A, Tamerius JD, Perzanowski M, Jacobson JS, Goldstein I, Acosta L, Shaman J (2014) Predicting indoor heat exposure risk during extreme heat events. Sci Total Environ 490:686–693

Quinn A, Kinney P, Shaman J (2017) Predictors of summertime heat index levels in New York City apartments. Indoor Air 27:840–851

Rothfusz LP (1990) The heat index "equation" (or, more than you ever wanted to know about heat index). SR 90–23. National Oceanic and Atmospheric Administration, National Weather Service, Office of Meteorology, Fort Worth. https://wonder.cdc.gov/wonder/help/Climate/ta_htindx.PDF

Schwartz J (2005) Who is sensitive to extremes of temperature?: a case-only analysis. Epidemiology. 16:67–72

Scott AA, Zaitchik B, Waugh DW, O'Meara K (2017) Intraurban temperature variability in Baltimore. J Appl Meteorol Climatol 56:159–171

Smargiassi A, Fournier M, Griot C, Baudouin Y, Kosatsky T (2008) Prediction of the indoor temperatures of an urban area with an in-time regression mapping approach. J Expo Sci Environ Epidemiol 18:282–288

Tamerius JD, Perzanowski MS, Acosta LM, Jacobson JS, Goldstein IF, Quinn JW, Shaman J (2013) Socioeconomic and outdoor meteorological determinants of indoor temperature and humidity in New York City dwellings. Weather Clim Soc 5:168–179

United States Global Change Research Program (2018) Fourth national climate assessment, Vol II: Impacts, risks, and adaptation in the United States. US Global Change Research Program, Washington

Vant-Hull B, Ramamurthy P, Havlik B, Jusino C, Corbin-Mark C, Schuerman M, Keefe J, Drapkin JK, Glenn AA (2018) The Harlem heat project: a unique media–community collaboration to study indoor heat waves. Bull Am Meteorol Soc 99:2491–2506

Watts N, Amann M, Arnell N et al (2018) The 2018 report of the Lancet countdown on health and climate change: shaping the health of nations for centuries to come. Lancet 392:247

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