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Heterogeneity in individually experienced temperatures (IETs) within an urban neighborhood: insights from a new approach to measuring heat exposure

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Abstract Urban environmental health hazards, including exposure to extreme heat, have become increasingly important to understand in light of ongoing climate change and urbanization. In cities, neighborhoods are often considered a homogenous and appropriate unit with which to assess heat risk. This manuscript presents results from a pilot study examining the variability of individually experienced temperatures (IETs) within a single urban neighborhood. In July 2013, 23 research participants were recruited from the South End neighborhood of Boston and equipped with Thermochron iButtons that measured the air temperatures surrounding individuals as they went about their daily lives. IETs were measured during a heat wave period (July 17–20), which included 2 days with excessive heat warnings and 1 day with a heat advisory, as well as a reference period (July 20–23) in which temperatures were below seasonal averages. IETs were not homogeneous during the heat wave period; mean IETs were significantly different between participants ($p<0.001$). The majority of participants recorded IETs significantly lower than outdoor ambient temperatures (OATs), and on average, the mean IET was 3.7 °C below the mean OAT. Compared with IETs during the reference period, IETs during the heat wave period were 1.0 °C higher. More than half of participants did not experience statistically different temperatures between the two test periods, despite the fact that the mean OAT was 6.5 °C higher during the heat wave period. The IET data collected for this sample and study period suggest that (1) heterogeneity in individual heat exposure exists within this neighborhood and that (2) outdoor temperatures misrepresent the mean experienced temperatures during a heat wave period. Individual differences in attributes (gender, race, socioeconomic status, etc.), behaviors (schedules, preferences, lifestyle, etc.), and access to resources are overlooked determinants of heat exposure and should be better integrated with group- and neighborhood-level characteristics. Understanding IETs for the population at large may lead to innovative advances in heat-health intervention and mitigation strategies.

Keywords Urban heat island · Boston · Heat · Individually experienced temperatures · Neighborhood · Heterogeneity

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Introduction

Continued urbanization and climate change pose significant environmental health hazards to city residents (O'Neill and Ebi 2009; Seto et al. 2012). Exposure to extreme heat is one such hazard, especially during prolonged periods of elevated temperatures ("heat waves") (Davis et al. 2003; Harlan et al. 2006; Anderson and Bell 2009; Hajat et al. 2010). In cities, urban form exacerbates summer temperatures via the urban heat island effect (Oke 1982; Chow et al. 2012; Georgescu et al. 2013). However, the spatial distribution of heat, the risk

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of heat exposure, and related health outcomes are uneven and reflect biophysical, social, and economic factors (Harlan et al. 2006; Uejio et al. 2011; Hondula et al. 2012).

Strategies for reducing heat and minimizing heat-health risks are often based on fixed-point, place-based, and/or population-level data sets (e.g., meteorological monitors at airports, remote sensing imagery, aggregated medical records). These study designs include an implicit assumption that population exposure can be estimated from data based on outdoor conditions. Further, some studies adopt the neighborhood (or corresponding administrative units of census tracts or zip codes) as an appropriate spatial unit to assess heat-health risk (e.g., Tan et al. 2010; Reid et al. 2012; Hondula et al. 2013a, b), implicitly assuming that individuals living in the same neighborhood or jurisdiction are generally exposed to the same air temperatures. Even interventions that target a specific group (e.g., elderly and isolated) within a neighborhood assume some level of homogeneity in heat exposure among group members.

At the scale of an individual, these three assumptions are flawed. Cities are spatially heterogeneous, and even within a single neighborhood, outdoor microclimate differences due to vegetation, street orientation, and building material may have real consequences for the temperatures experienced by an individual (Cadenasso et al. 2007; Dousset et al. 2011; Middel et al. 2014). In addition, access to resources within and beyond one's home and neighborhood and, relatedly, individual behavior, preferences, and schedules may vary greatly among residents, creating large contrasts in exposure across individuals (Basu and Samet 2002; Small 2004), particularly in more diverse and heterogeneous neighborhoods (Jacobs 1961; Small 2004; Maly 2005; Freeman 2011). Many individuals spend a majority of their time indoors in climate-controlled settings (Brasche and Bischof 2005), while others may work and live in settings without access to climate control, such as air-conditioning (O'Neill et al. 2005; Gubernot et al. 2013). Because indoor temperatures depend greatly on dwelling quality and characteristics (Smargiassi et al. 2008; Oikonomou et al. 2012), it is difficult to predict the temperatures that an individual will experience as they move between indoor and outdoor spaces. Individuals may also experience a wide range of temperatures as they move around within the city or leave the metropolitan area to visit family, friends, parks, shopping malls, or other amenities. Thus, an individual's mobility and the scale of his or her social network (quantity and locations of contacts) may also influence or create intra-neighborhood variation. Together, the considerations above suggest that patterns in heat exposure may be difficult to reduce to a neighborhood population or its social groups.

While considerable advances have been made in our understanding of the risks posed by extreme heat, there is a paucity of data regarding individual-level exposure. To our knowledge, no study has recorded temperatures simultaneously experienced by multiple individuals as they go about their daily lives. We contend that this gap in knowledge limits the potential effectiveness of heat-health interventions. Efforts aimed at mitigating heat in the *places* that are hottest within cities might target locations different from those where human exposure to outdoor temperature is greatest. For example, in terms of daily averages, urban heating effects lead to higher temperatures in dense, downtown, commercial districts where people may actually spend a majority of their time in air-conditioned buildings (Oke 1982). However, the diurnal variability beyond these mean patterns (Dousset et al. 2011) combined with complex activities and movements of urban individuals further challenge our ability to identify the places where heat exposure is greatest.

Viewing personal exposure as a critical but unmeasured heat risk factor, for this pilot study, we collected direct measurements of individually experienced temperature (IET) to assess the following: (1) how IET varies between individuals living within the same neighborhood, (2) how IET compares to fixed-point outdoor measurements, and (3) how IET varies between normal summer conditions and an extreme heat event.

Materials and methods

Study location and population

This study focused on the South End neighborhood of Boston, Massachusetts (hereafter BSE), a diverse central city neighborhood in terms of income, age, race, and occupation. Over the past four decades, this neighborhood has undergone waves of gentrification and is currently at an advanced stage in which the community has shifted toward wealthier residents, property values have risen greatly, renovation has altered much of the neighborhood landscape, and many original poor and working-class residents have been displaced (Small 2004; Brown-Saracino 2010). Meanwhile, BSE has maintained the greatest density of low-income public housing developments (over 4000 units) relative to other Boston neighborhoods (BHA n.d.). The most recent American Community Survey (2013) estimates that 21.9 % of households are living below the federal poverty line, while 21.5 % of household incomes exceed $150,000. Demographically, BSE is 53.1 % white, 12.3 % black or African-American, 17.5 % Asian, and 14.4 % Hispanic or Latino. The median age is 32.4 years. In total, 4.3 % of households in the neighborhood were identified as same-sex (US Census Bureau). Twenty-three participants were recruited from this neighborhood, 19 of whom lived in separate residences and 2 pairs of whom lived together. Surveys and exit interviews were used to collect additional information from participants about demographics (age, race, gender), housing status, activities during the week, lifestyle, occupation, orientation toward the neighborhood, uses of indoor and outdoor spaces, as well as public and private cooling resources. Eighty-seven percent of participants (20 out of 23) filled out surveys, and 78 % of participants (18 out of 23) participated in exit interviews. Every participant engaged in at least one such additional qualitative activity.

Participants were diverse in terms of age, income, housing type, and gender. Ages ranged from 25 to 79. Nine participants identified as male, while 14 identified as female. Twenty-six percent of participants identified as Black or African-American, and 74 % identified as white. Three participants had lived in BSE for more than 40 years, and 12 had moved to the neighborhood within the past decade. Twenty out of 21 participants that disclosed information about home cooling resources had access to (but did not necessarily use) air-conditioning during the study period. Recruitment took place during June and July of 2013 and occurred at community meetings and senior centers, through flyers distributed on the street by the researcher, and via study information bulletins posted in apartment buildings and neighborhood businesses. Study approval was obtained from the Institutional Review Board at Boston University (protocol 3152X) prior to participant recruitment, with written informed consent received from all participants.

Procedure

The study took place during a 1-week period from 20:00 July 17 to 20:00 July 24, 2013 to capture IETs under warm summer conditions. Boston experienced a heat wave from July 15 through July 20, with National Weather Service's excessive heat warnings in effect for July 18 and 19. National Weather Service's heat advisories were issued for July 15, 16, 17, and 20. Because the heat wave occurred during the week in which data collection was planned, two smaller time periods were defined to contextualize IETs during excessive and cooler summer conditions. The heat wave period is defined as 20:00 July 17 to 20:00 July 20 and a reference period as 20:00 July 20 to 20:00 July 23. Each research participant was equipped with a Thermochron iButton (DS1921G-F5#, see Supplemental Material Fig. S1). This is a small and light mobile sensor (<20 mm diameter, <7 mm thickness, 3.3 g) that measured and recorded instantaneous air temperature at 5-min intervals during the study week with an accuracy of ±1 °C and a thermal response time of 130 s (EDS 2012; Sullivan and Collins 2009). The IETs were converted to hourly averages for each participant by taking the mean of the 12 values centered on the top of each hour. The average for 7:00, for example, represents the mean IET for the period 6:30 to 7:25. All times are reported in local daylight time (LDT).

iButtons were attached to key ring mounts and connected to a carabineer. Participants were asked to clip their iButtons to a belt loop or bag such that the device was continuously exposed to the surrounding air. Participants were also asked to record any periods of time in which they were not carrying their iButtons (these data were removed prior to analysis). Thus, iButtons recorded a time series of ambient temperatures experienced by participants, both indoors and outdoors. This IET time series approximates each participant's heat exposure (Basu and Samet 2002). Two iButtons were placed in trees in BSE (monitor 1: 42.340836° W, 71.066864° N; monitor 2: 42.341211° W, 71.077122° N) during the study week at roughly 2 m above the ground in inconspicuous locations accessible to the researcher. The time series of temperatures collected by these monitors was averaged to construct the outdoor ambient temperature (OAT) profile of BSE during the study week. Hourly temperature data for the study period were also obtained from Boston Logan International Airport (KBOS) to construct the OAT profile of the metropolitan Boston area that is used for the activation of excessive heat warnings or heat advisories.

Statistical analyses

Between-subject IETs were compared using an analysis of variance (ANOVA) test during the heat wave period (hours 1–72) and the reference period (hours 73–144). Initial hypothesis testing of equal variances across groups was completed with the Brown-Forsythe test. If this hypothesis was rejected, we used the Welch test to examine differences in the mean IET between participants; otherwise, the cases with equal variances applied the ANOVA test. This was repeated for the entire heat wave period and reference period as well as for two subsets of each period that included only daytime or nighttime hours (12:00 to 19:00 and 23:00 to 6:00, respectively, corresponding to periods of anticipated maximum and minimum outdoor temperatures). A level of statistical significance of $p<0.05$ was used for the ANOVA and Welch tests.

We next compared each participant's IET data to the OAT measurements recorded by iButtons located in BSE with a two-tailed t test assuming unequal variances. This test was repeated for the heat wave and reference periods as well as the daytime and nighttime subsets of each period. To account for multiple comparisons, we adjusted the p value necessary for statistical significance with the Bonferroni correction, dividing p by the number of tests (0.05/23).

Finally, we compared each participant's IET data between the heat wave period and the reference period to examine if participants experienced statistically significant different temperatures between the two periods of markedly different meteorology (i.e., heat wave and reference periods). Using a two-tailed paired t test, each participant's IET was compared between the two periods for all hours and subsets of the heat wave and reference periods representing daytime and nighttime only. The Bonferroni correction was again used for determining statistical significance ($p<0.05/23$). All statistical tests were performed in the MATLAB computing environment (version R2013a).

Results and discussion

Throughout the study period, iButtons successfully recorded IETs and OATs in Boston's South End. iButtons were generally found to be convenient, simple, and useful devices to conduct this experiment, and a majority of the participants (21 out of 23) carried their iButtons for over 85 % of the study period, with 11 of those participants carrying their iButtons 100 % of the time. The remaining two participants did not collect 26 and 41 % of their IET data. Overall, data were collected for more than 95 % of possible observations. OATs in BSE were between 26.5 and 37.2 °C during the heat wave period (mean 30.6 °C), whereas during the reference period, OATs ranged between 21 and 30.6 °C (mean 24.1 °C) (Fig. 1(a)).

Neighborhood heterogeneity

Mean IETs fluctuated diurnally with higher values observed closer to midday and lower IETs in the overnight hours (Fig. 1(a)). A diurnal pattern was also evident in the variability of IETs between participants, with higher standard deviations observed during the daytime and afternoon hours and lower values overnight (Fig. 1(b)). Time series of selected individual participants' IETs demonstrated large differences in temporal variability (Fig. 2), directly driven by variations in daily schedules, lifestyles, and access to air-conditioned spaces, as informed by responses to survey instruments. Participant 11, for example, did not have air-conditioning at home and spent much of the day inside. Participant 21 worked from 9:00 to 17:00 in an air-conditioned office, while participant 2 spent the day going inside and outside of various locations including a fitness center and a library. During the heat wave period, mean IETs were significantly different between participants (all hours, $p<0.001$, Fig. 3). Daytime and nighttime analyses also revealed significant differences between participant's IETs during the heat wave period ($p<0.001$, Supplemental Material Figs. S2 and S3). During the reference period, mean IETs were also significantly different between participants for all hours as well as daytime and nighttime hours ($p<0.001$ for all three time periods), indicating that heterogeneity in thermal experience is not necessarily a phenomenon unique to heat waves.

The study neighborhood (BSE) had slightly higher temperatures compared with the airport (KBOS) during the heat wave (Fig. 3), which likely arose because of urban heating effects. Namely, BSE is closer to the urban core than KBOS, which is located near Massachusetts Bay. Intracity variation in neighborhood temperatures is a documented characteristic of the urban heat island and places some residents at greater risk than others with respect to where they live (Klinenberg 2002; Hondula et al. 2012; Harlan et al. 2013). In addition to these intracity variations, the results presented above also document an intra-neighborhood variation in IETs, both during heat wave and background summer conditions.

Comparing OAT and IET

For some participants, visual inspection of IETs suggested only a minimal relationship with OAT and an inverse relationship for the individual (participant 21) that worked in a cold office building (Fig. 2). However, all participants' mean IETs during the heat wave period were lower than the mean OAT, and this difference was statistically significant for 20 out of 23

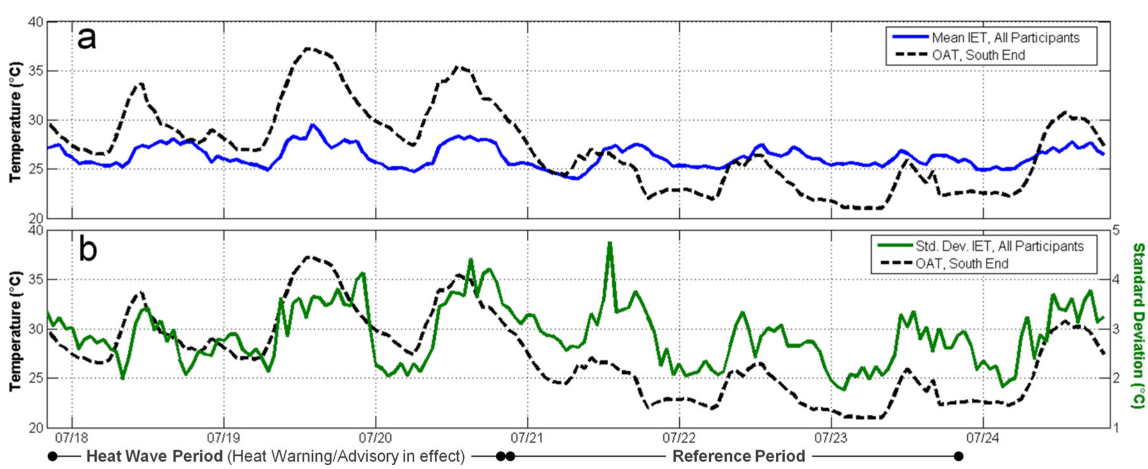

Fig. 1 Time series plots comparing individually experienced temperature (*IET*, *solid lines*) and outdoor ambient temperature (*OAT*, *dashed lines*) in Boston's South End (BSE), July 17–24, 2013. *a* The mean IET of 23 study participants aligned with OAT; *b* the standard deviation (*right axis*) of participants' IET aligned with the OAT, as shown in *a*

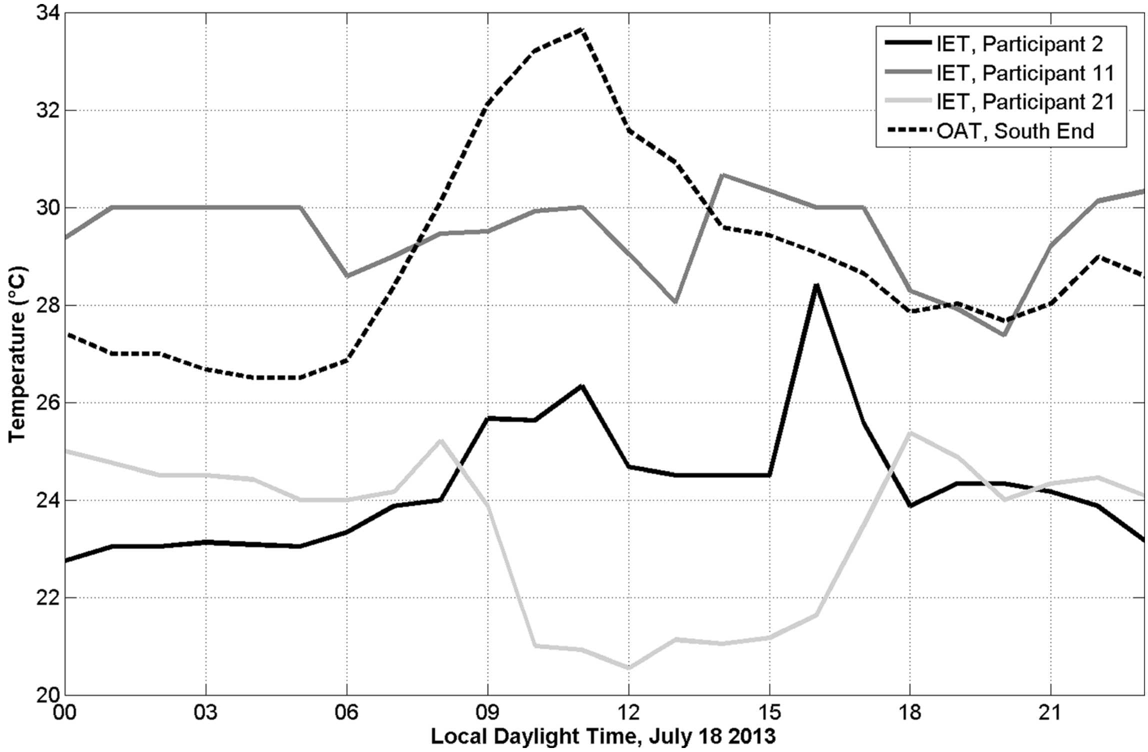

Fig. 2 Individually experienced temperature (*IET*) of the three selected study participants (*solid lines*) as well as outdoor ambient temperature (*OAT*, *dashed line*) in Boston's South End (BSE) on July 18, 2013

participants (Fig. 3). During the daytime hours, IETs were significantly lower than OATs for 18 out of 23 participants. Nighttime contrasts between IETs and OATs were lower in magnitude. Fourteen participants had IETs that fell significantly below OATs, while one participant had IETs significantly above OATs during the nighttime hours, perhaps because this participant lived on one of the higher floors of her apartment building and preferred to use fans and natural

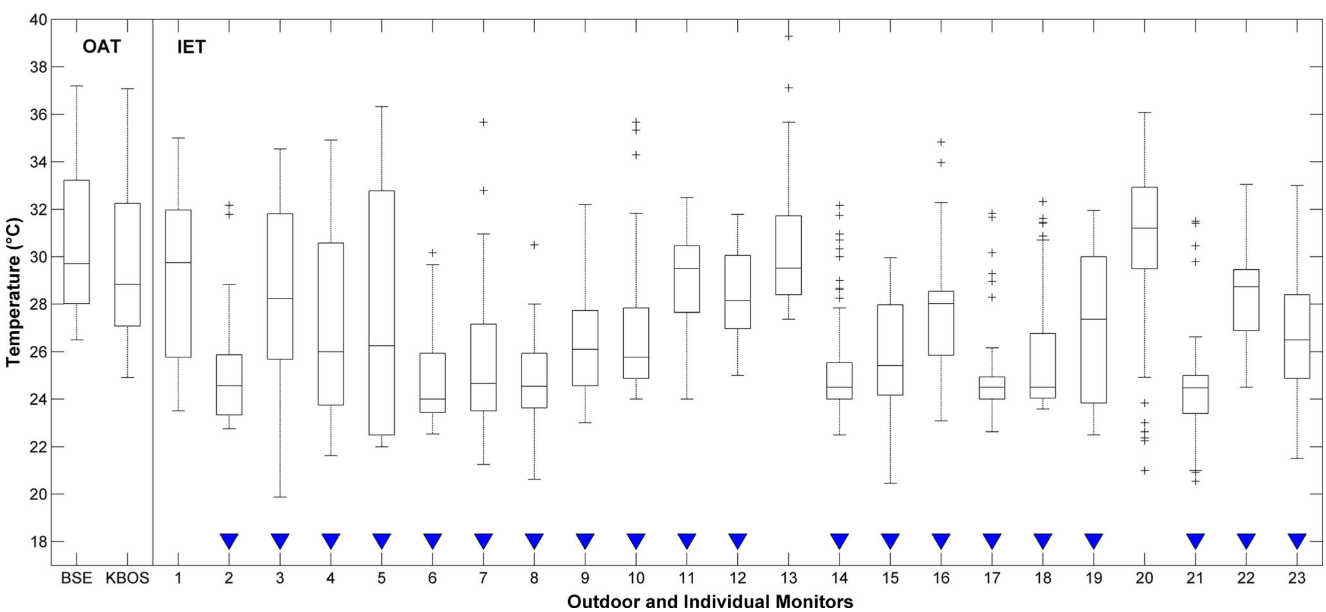

Fig. 3 A comparison of individually experienced temperature (*IET*) and outdoor ambient temperature (*OAT*) in Boston's South End during a heat wave period, July 17–20, 2013. The *two left-hand boxes* represent a fixed-point monitor (OAT), with the *remaining boxes* representing a single study participant's IET, fixed-point measurement. *BSE* Boston's South End, *KBOS* Boston Logan International Airport. *Triangles* indicate significantly lower IETs than OATs for each study participant, as measured in BSE

Table 1 Contrasts between IETs and OATs during the heat wave period

Period	Differences between mean OAT and mean IET for all participants (OAT-IET) [95 % confidence interval]	Range of differences between mean OAT and mean IET for all participants (OAT-IET)
All hours	3.7 °C [3.0, 4.5]	0.1 °C to 6.3 °C
Day hours	5.1 °C [4.1, 6.0]	0.8 °C to 8.9 °C
Night hours	2.2 °C [1.4, 3.1]	−1.1 °C to 4.9 °C

ventilation rather than air-conditioning (Supplemental Material Figs. S2 and S3). Contrasts between IETs and OATs during the heat wave period are summarized in Table 1.

Compared with mean IETs during the reference period, mean IETs during the heat wave period were 1.0 °C higher [95 % confidence interval 0.4–1.6]. This difference is statistically significant, but not greater than the iButton accuracy (±1 °C). The mean OAT during the heat wave period was 6.5 °C higher than the mean OAT during the reference period. More than half of participants (14 out of 23) did not experience statistically different temperatures between the two periods for all hours (Fig. 4). During daytime hours, the difference in mean IET between the heat wave period and the reference period was 1.3 °C [0.5–2.1], which also falls within the range of measurement error. As with the comparison of all hours, more than half of the participants (15 out of 23) did not experience significantly different temperatures between the periods. During nighttime hours, the IET difference between the heat wave period and the reference period was 0.2 °C [−0.3 to 0.6] and this difference was not statistically significant. In comparison to both daytime and all hours, the nighttime hours demonstrated the highest number of participants (16 out of 23) in which IETs between the periods were not significantly different (Supplemental Material Figs. S4 and S5).

When individuals were active and could make choices about where they spent their time, both inside and outside, outdoor temperatures did not estimate actual personal heat exposure with much accuracy. The greatest variability of IETs was observed during daytime, reflecting heterogeneity within the study sample in how much time individuals spent outside, where that time was spent, and what cooling resources those individuals could access (Small 2004; Brasche and Bischof 2005; Harlan et al. 2006). In the present study, 18 out of 23 participants (78 %) had daytime IETs that were significantly different from OATs during the heat wave period (Supplemental Material Fig. S2). The five individuals with similar IETs and OATs reported spending a large portion of their time outside each day, for example maintaining a car (participant 1), sitting on a bench outside the library (participant 5), or going on long walks (participant 20). Most participants (15 out of 23 or 65 %) did not experience significantly different daytime conditions between the heat wave and reference periods (Supplemental Material Fig. S4). Participant 12, who experienced almost no difference between the two periods, reported during the exit interview that she mostly stayed at home during the heat wave and even sat in front of the air-conditioning unit in her television room instead of going to work on July 19. Indeed, participant 12 worked half days and had the agency to alter her schedule when it was hot. This adaptive strategy lowered this participant's IET during the heat wave period such that it was similar to the IET during the reference period. OATs also slightly overestimated IETs in a study of

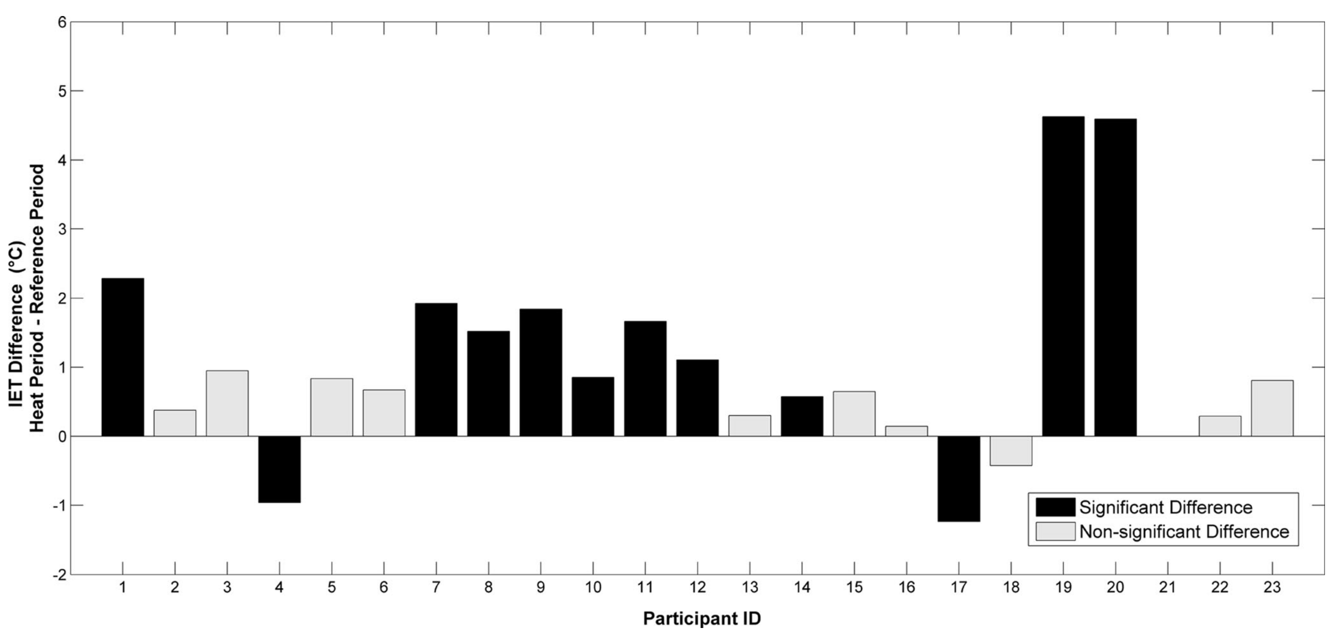

Fig. 4 The difference in mean individually experienced temperature (*IET*) for each of the 23 subjects in Boston's South End (BSE) between a heat wave period (July 17–20, 2013) and reference period (July 20–24). *Positive values* indicate the IETs as higher during the heat wave period, with *black shaded bars* representing statistically significant differences in IETs between the two periods and *gray* being insignificant

elderly residents of Baltimore whose temperatures were measured during individually unique periods of observation in the warm season (Basu and Samet 2002). When individuals were active and could make choices about where they spent their time, both inside and outside, outdoor temperatures did not estimate actual personal heat exposure with much accuracy.

Nighttime IET is also a potentially important indicator of heat-health risk (Dousset et al. 2011; Laaidi et al. 2012). At night, the built form of the city results in decreased long-wave energy transfer from the urban boundary layer into the atmosphere as compared with heat loss from surrounding rural areas, which results in higher relative urban nighttime temperatures. These elevated minimum temperatures can make it more challenging for people to physiologically recover from high daytime temperatures (Harlan et al. 2006). Yet, at night, individuals tend to be less mobile, in their residence, and have fewer agencies to modify their thermal environments compared with the daytime. Past research suggests that indoor and outdoor temperatures are positively related, especially during warmer periods (Klinenberg 2002; Tamerius et al. 2013; Nguyen et al. 2014). In the present study, 15 out of 21 participants (71 %) had nighttime IETs that were significantly different from OATs during the heat wave period and 16 out of 23 participants (69 %) did not experience significantly different nighttime conditions between the heat wave and reference period (Supplemental Material Figs. S3 and S5). Ownership and use of home air-conditioning characterizes participants that fit into both categories. Preference for natural ventilation and living on the top floor of a building were some characteristics of participants that did not fit into either category.

When individuals were largely at home, therefore, OATs did not accurately estimate indoor IETs. Rather, factors such as dwelling quality and access to and use of air-conditioning and ventilation may better explain variation in nighttime IET (Oikonomou et al. 2012; Franck et al. 2013). Thus, material conditions, such as home air-conditioning access, can matter greatly and play a role in homogenizing IETs. Yet, while material conditions are important at night and during heat waves, they had a weaker association with IETs during the day. Rather than material conditions or OATs, daytime IET could be better explained by factors such as time spent outside, daily schedule (as it relates to occupation and other factors), and behavior.

Integration of individual-level analysis

The results presented suggest that heterogeneity of IETs can exist within an urban neighborhood during both a heat wave and more typical summer conditions. Further, outdoor temperatures misrepresent individual heat exposure both during the day, when individuals are active and mobile, and at night, when individuals are mostly inside. Past research has identified individual attributes including age, preexisting medical conditions, marital status, gender, educational attainment, and race as important in determining heat-health risk in certain locations (e.g., Medina-Ramón et al. 2006; Bell et al. 2008; Stafoggia et al. 2008). Indeed, some patterns in IETs were detectable due to aforementioned attributes. Participants living in subsidized housing had higher daytime mean IETs during the heat wave period compared with participants living in private market housing (ANOVA, $p<0.05$), despite the prevalence of home air-conditioning among participants. Older participants had higher IETs than younger participants (ANOVA, $p<0.05$). Weaker associations were found for gender (ANOVA, $p<0.1$) and race (ANOVA, $p<0.1$). These trends suggest that while attributes may establish the range of temperatures that an individual may experience, other practices may expose that individual to higher or lower temperatures than predicted based on his or her characterizing attributes.

Little attention has been focused on integrating individual attributes and behaviors in regards to heat exposure. Research that addresses coping mechanisms recognizes that hotter areas and marginalized populations in the aggregate have less access to cooling resources (e.g., Klinenberg 2002; Harlan et al. 2006; Uejio et al. 2011); however, these considerations do not fully capture the options available to different individuals within those areas or populations (Wilhelmi and Hayden 2010). Social context, at the scales of person, building, block, neighborhood, or city, may explain how risk factors are related to heat exposure and access to cooling resources during the day (Klinenberg 2002). For example, in a gentrifying neighborhood such as BSE, long-term residents may spend more time on the street socializing, while newer residents may spend more time at home or in select commercial locales, such as coffee shops (Levy and Cybriwsky 1980). In this example, the attribute of being a long-term resident may expose an individual to higher temperatures compared with newer residents. Participants 3, 4, and 5, who had all lived in BSE for over 55 years, had among the highest daytime IETs (Supplemental Material Fig. S3). Participant 3 reported that on hot days, he enjoyed spending time under shade trees with friends rather than staying inside. A person's gender, race, and socioeconomic status may affect that individual's access to and use of air-conditioned buildings, such as homes, private businesses, cooling centers, parks, and pools, as mediated by local social and cultural constraints and opportunities. Over time, BSE has become increasingly white and median incomes have risen, thus changing the groups of people that use and have access to cooling resources (US Census Bureau).

Yet the vast variability in IETs suggests that even if demographic, geographic, social, and cultural factors impose some structural patterns in IETs, within-group variation may also exist. Consider our observations of two of the long-term residents from the study sample, both of whom are black, elderly, and male; participant 4 spends some of the day in an air-conditioned senior center, and participant 3 spends the day outside. Alternatively, consider two newer residents from the sample, both of whom are white, middle-aged, and female; participant 8 spends hours outside walking her dog each day, and participant 21 does not. The neighborhood as a symbolic entity may be valuable because its social context provides specific and unique mechanisms, like gentrification or public housing, through which individual behaviors and attributes are played out (Wilhelmi and Hayden 2010). Consider participant 20, for example, who was male, unemployed, and lived in subsidized housing. He preferred to spend his many hours of unoccupied time in the park and taking walks rather than staying inside his tiny apartment. Other mechanisms including access to and use of material resources (such as parks and air-conditioning) and social and cultural dynamics (such as fear of or comfort spending time outside) may be systematically regulated through such neighborhood social processes (Klinenberg 2002). It is important to note that heterogeneity in IETs is likely not equal in all urban neighborhoods, especially for those that are more demographically homogeneous than BSE (Maly 2005). However, it is likely that heterogeneity exists to some degree in many or all neighborhoods.

Given that this pilot study is, to the best of our knowledge, the first to document IETs for multiple individuals simultaneously moving through urban areas, we offer several recommendations for future research efforts and acknowledge limitations of this project. First and foremost, the results of this study suggest that individual differences are important determinants of heat exposure, but future experiments with larger samples, longer sampling periods, and in other study locations are necessary to determine their generalizability. With only 1 week of data, we were unable to account for the effect of day of week. Strategic sampling of different urban neighborhoods and vulnerable populations would be helpful for gaining insights into the true mechanisms that drive heterogeneity in different settings and cause some individuals to be at higher risk when extreme heat occurs. There were challenges in data collection that could be redressed in subsequent efforts, including ensuring the validity of metadata from participants regarding when they did and did not carry their iButton and reducing the influence of radiative effects on iButtons when they were exposed to sunlight. Radiation is an important component of the human energy balance (e.g., Vanos et al. 2012), but we did not specifically determine radiative effects on iButtons, introducing some error into the IET data presented herein. Connecting IET data with human energy budget components and models is an important future step to make the IET approach more directly applicable for understanding how IET influences core temperature and thus the risk of various specific heat-health outcomes (e.g., Malchaire et al. 2000). Physiological differences in how individuals respond to heat, consequent thermal comfort, and adaptive capacity are also likely important components in IET generation. Concepts such as acclimatization to the neighborhood environment and social network scale can also be included into IET analyses to further provide social context. Finally, additional experiments should include detailed activity data from participants to better understand the drivers of IET differences. These final points are the subject of ongoing research efforts.

In summary, the IET data collected suggest that heterogeneity in individual heat exposure exists within an urban neighborhood and that outdoor temperatures may misrepresent experienced temperatures during both background summer conditions and heat waves. In particular, for most participants, the occurrence of a heat wave had little impact on nighttime IETs when compared with a reference period. While these specific findings may not be applicable in other locations, they highlight broad limitations in our current understanding of heat exposure and risk that can be addressed through the IET framework. We have also discovered that some of the attribute-based differences in risk reported elsewhere (e.g., related to age) may in fact result from differences in thermal experiences and not solely emerge from other drivers including physiological susceptibility and adaptive capacity.

Many authors have called for the integration of analyses at the city, neighborhood, and household scale as well as the coupling of social and biophysical data to better understand heat risk and vulnerability (Wilhelmi and Hayden 2010; Huang et al. 2011; Harlan et al. 2013). The IET approach presented in this study allows for novel analysis of individual-scale data that recognizes differential access to resources, personal attributes, and the movement of individuals between indoor and outdoor spaces, within and outside of their neighborhood of residence, and through a thermally and socially heterogeneous urban environment. All these factors are potential determinants of heat-health outcomes (Tamerius et al. 2013) and should be integrated into heat intervention policy and practice (Basu and Samet 2002; White-Newsome et al. 2014), including the design and implementation of heat warning systems (Pascal et al. 2011; Zhang et al. 2012; Hondula et al. 2013a, b; Lam et al. 2013). Through the multi-scalar and multi-dimensional lens of IET, researchers, planners, communities, and individuals can better understand and respond to heat-health risk so as to make the city a better place to live for everyone.

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