THE HARLEM HEAT PROJECT
A Unique Media–Community Collaboration
to Study Indoor Heat Waves

BRIAN VANT-HULL, PRATHAP RAMAMURTHY, BROOKE HAVLIK, CARLOS JUSINO, CECIL CORBIN-MARK, MATTHEW SCHUERMAN, JOHN KEFF, JULIA KUMARI DRAPKIN, AND A. ADAM GLENN

A consortium of media partners, a community action group, and academic scientists studied the impact of indoor residential heat waves in the New York neighborhood of Harlem.

In an average year, high temperatures kill more people in the United States than all other weather-related phenomena combined (NOAA 2016), and in New York City two-thirds of heat-related deaths occur at home (Walters et al. 2014). Those most at risk are the ill and elderly (Basu 2009), who tend to be home throughout the day, yet few studies capture indoor residential temperatures in non-air-conditioned homes (Smargiassi et al. 2008; White-Newsome et al. 2012; Yushino et al. 2006). This is likely because placing sensors inside homes is intrinsically intrusive, so any such study must surmount the divide between academia and the public. Recent studies in New York City have addressed this by using patients of asthma studies, families of Head Start students, even paramedic visits (Quinn et al. 2017, 2014; Uejio et al. 2016; Tamerius et al. 2013). These previous studies differ from the current work in that they either focus on the effects of air conditioning or do not record its presence, and though hundreds of residences were involved, the sensors remained in place for less than two weeks.

The Harlem Heat Project described here is unique in its genesis as a consortium between media partners and community groups. The human interest of the health effects of heat waves was so high, and long-term scientific data on indoor temperatures of non-air-conditioned residences in New York City so sparse, that members of the local media started an indoor temperature measurement program on their own. Scientific advisors for data analysis were brought in once the basic outlines were in place. The human impact stories motivated by this project can be found on the websites of AdaptNY (www.AdaptNY.com).

Publisher’s Note: On 7 January 2019 this article was revised to correct Equation (1).
INTRODUCING THE PARTNERS: A SCIENCE–MEDIA COLLABORATIVE PARADIGM

The unique collaboration between media and community groups enhanced the access of the research team to residences: providing familiarity and visibility. Such team diversity is expected to prove increasingly vital to studies related to human impacts (Hamstead et al. 2016). The various organizations involved in the Harlem Heat Project are described here.

AdaptNY—An experimental news service that aims to curate, document, and foster conversation about how New York will adapt to the coming challenges of climate change. Launched in 2013 to explore flood resilience in New York City, AdaptNY shifted focus in the spring of 2016 with a new grant to report on how specific neighborhoods were coping with other, nonflood types of climate change risks. AdaptNY partners with the City University of New York (CUNY) Graduate School of Journalism, the Gotham Gazette, Document Cloud, and recently with the media partners listed below. (www.adaptny.org)

ISeeChange—Founded in 2012 as the nation’s first community crowd-sourced climate and weather journal empowering users to document environmental changes, share observations, and discuss impacts over time. Through their environmental reporting platform—available online and through a mobile app—ISeeChange combines citizen science, participatory public media, and satellite and sensor monitoring to observe and collect baseline data on how weather and climate are changing daily life. ISeeChange challenges traditional top-down models of sharing climate information by starting with community members first, positioning them as experts on their own environments. Community posts are synced with data, enabling ground truthing and baseline data to power unique collaborations with public service, media, and science partners. (www.iseechange.org)

WNYC—New York’s flagship public radio station, broadcasting programs from National Public Radio (NPR), American Public Media, Public Radio International, and the British Broadcasting Corporation (BBC) World Service, as well as a wide range of award-winning local programming. New York Public Radio’s commitment to community is an important part of its mission. The station’s dedication to developing partnerships, promotions, and events extends its mission to the larger community, striving to reflect the diverse voices found within the New York City and tri-state area. (www.wnyc.org)

WE ACT for Environmental Justice—Started in 1988 when three community leaders saw that environmental racism was rampant in their West Harlem neighborhood, and they demanded community-driven political change. Today, the organization has grown to over 16 staff members and two locations in New York City and Washington, D.C., and is considered an active and respected participant in the national environmental justice movement. Since the beginning WE ACT’s mission has been to implement collaborative, nonhierarchical environmental health research between the community and scientists. (www.weact.org)

CREST Institute at the City College of New York—The NOAA-affiliated Cooperative Center for Earth System Sciences and Remote Sensing Technologies (CREST) aims to conduct research; and educate and train students, early career scientists, and engineers in NOAA-related science missions to help create a diverse science, technology, engineering, and mathematics (STEM) workforce for NOAA, associated contractors, academia, and the private sector. This is facilitated by the center’s location: the City College of New York, the city’s leading minority-serving research institution located in northern Manhattan. (www.ccny.cuny.edu/crest/)

Detailed scientific results and crucial organizational lessons learned for community-based science are described below, but since urban science is new to many readers, we begin with a brief introduction to the urban heat island and its health effects. The physical influences underlying the urban behavior of outdoor temperatures have been well documented (Oke 1982; Grimmond and Oke 1999; Rizwan et al. 2008). Since urban surfaces do not retain water and are sparsely vegetated, they benefit little from evaporative cooling. Concrete, brick, and metal conduct heat more efficiently than soil and wood, increasing heat storage so that heat is retained at night and temperatures are modulated throughout the diurnal cycle in comparison to rural areas. During the day the urban flow of heat into storage may offset the lack of evaporative cooling somewhat, but at night as air temperatures drop below surface temperatures, the heat retained in these structures flows back out. Tall buildings capture radiation from neighbors, creating a radiative heat trap that slows nocturnal cooling in street canyons. Waste heat from human activity contributes to this urban heat island mainly through evaporated water from cooling towers (Gutiérrez et al. 2015; Ichinose et al. 1999). The result is that urban temperatures are on average elevated above rural temperatures, with the difference reaching a maximum at night (Montávez et al. 2000; Rizwan et al. 2008). The spatial temperature structure of cities varies on the scale of 100 m (Weng et al. 2004), meaning that the heat “island” may be better described as an archipelago (Rosenzweig et al. 2006; Vant-Hull et al. 2014; Grimmond 2007). The common approach of categorizing urban heat island effects by satellite

adaptNY), WNYC (www.wnyc.org/series/harlem-heat-project), and ISeeChange (www.iseechange.org/investigations/5797f94f787db5d27a4bd77d).

Unauthenticated | Downloaded 08/10/23 07:42 AM UTC
infrared measurements can be misleading, for most infrared radiation comes from surfaces that are typically not in equilibrium with air temperatures by day, though they are more representative at night (Dousset et al. 2011). However, if both the air temperature and the radiative environment of urban surfaces are accounted for, a clearer picture can be obtained of how the population is affected by microvariations in the urban heat island (Smargiassi et al. 2009).

Elevated nighttime urban temperatures can induce convergence and a city-scale circulation (Haeger-Eugensson and Holmer 1999; Bornstein and Lin 2000). This picture is complicated in coastal cities like New York by sea breezes (Gedzelman et al. 2003), where the effects of heat waves cannot easily be estimated based on weather models that are too coarse to capture such details. At the time of writing, physical models with high enough resolution to capture individual building characteristics are limited by computing power to domains of a few city blocks (Gal 2014), while models that encompass entire cities have resolutions on the order of a kilometer (Gutiérrez et al. 2015), which is sufficient to capture sea breeze but not finer structure. Observational networks are limited by the cost of deploying multiple instruments, so the resolution of outdoor urban measurements is even coarser than that of models. Though this reflects the state of meteorology at large, it would seem the concentration of population in the cities merits a higher density of observations.

Indoor temperatures are yet another step removed from the larger-scale weather patterns. If we focus on non-air-conditioned residences, the temperatures are dominated by air exchange and solar irradiation through the windows, plus heat storage by the building (White-Newsome et al. 2012; Quinn et al. 2014, 2017). The effects and usage of windows are modified in highly urbanized areas, where residents are less likely to open windows because of noise or fear of crime, and shading from eaves is rare (Vellei et al. 2017; Coley et al. 2012). In a study in New York City, only one-fifth of residents opened their windows at night even when outdoor temperatures were lower than indoor temperatures (Quinn et al. 2017), though this was in a sample where most residents had window air conditioners. The lower room count in tenement residences also correlates to higher temperatures, likely as a result of interior circulation (Tamerius et al. 2013). Observations generally show that while outdoor temperatures change on the scale of hours, as a result of thermal inertia indoor temperatures change on the scale of days; and in summer the daily temperature averages of both non-air-conditioned and air-conditioned residences are higher than outdoor daily averaged temperatures (Yoshino et al. 2006; Smargiassi et al. 2008; White-Newsome et al. 2012; Quinn et al. 2017). A time lag on the order of a day between indoor and outdoor temperatures has commonly been observed (Smargiassi et al. 2008; Quinn et al. 2014). Indoor temperatures in inner-city Montreal, Canada, were seen to increase with floor level (presumably because of more sunlight) but decrease again above the fourth floor, an effect attributed to increased ventilation (Smargiassi et al. 2009), though evidence for the floor effect has been contradictory in New York City (Tamerius et al. 2013; Quinn et al. 2017). We have observed most of these phenomena in our pilot project described below.

The average effects of high temperatures on human health vary with city. Every city has an optimum outdoor daily averaged temperature for minimum mortality set not just by climatic conditions but by human adaptation, such as home construction, powered temperature controls (Curriero et al. 2002), and physiological adaptation (Kinney et al. 2008). Through the last four decades, residential air conditioning has penetrated southern cities to such an extent that mortality always decreases as temperature increases, but though the mortality rate has dropped in northern cities, a moderate optimum temperature is still evident (Davis et al. 2003; Sheridan and Dixon 2017). As outdoor temperatures cool below this optimum, the mortality in cities such as New York increases relatively gently compared to the sharp rise in mortality as the temperature warms above the optimum, producing a characteristic hook-shape dependence of mortality on temperature (Curriero et al. 2002; Kinney et al. 2011). As these studies show mortality in cities of the northern half of the U.S. East Coast increasing at roughly 6% of the baseline for every 1°C rise in temperature above the optimum (ranging from 19°C to 21°C for these cities), it becomes imperative to understand the exact physiological effects of a heat wave—effects that cannot be clearly understood using outdoor temperatures alone. Unfortunately, heat warning metrics used by the National Weather Service are not tuned to urban areas (Metzger et al. 2010).

Within the borough of Manhattan in New York, the Harlem community is particularly prone to heat-related health impacts for both physical and socioeconomic reasons (Madrigano et al. 2015; NYC Health 2017). Compared to the rest of the island, residential buildings in Harlem tend to be lower (average 4.6 floors vs 6.3 floors) and slightly wider spaced (average building plot fraction of 0.68 vs 0.73), so sunlight...
illuminates a larger fraction of the urban canyons [statistics calculated from the New York City (NYC) Planning Department Plant Variety (PLUTO) database; NYC Planning 2017a]. A 30–35-m-high ridge runs along the western side of Harlem, reducing prevailing surface winds; on such days air has more time to equilibrate with sun-heated surfaces than in less sheltered neighborhoods. Winds are generally from the south during a heat wave, so by the time surface air parcels reach Harlem, they have been heated by buildings in the southern portions of the city; these parcels tend to form a low-level inversion, cutting off convective mixing with cooler air from above (Ramamurthy et al. 2017). These combined effects make Harlem one of the warmer neighborhoods in the city (Vant-Hull et al. 2014; Rosenzweig et al. 2006).

But locally elevated temperatures are only a small contributor to the locally elevated heat-related health impacts. Socioeconomics plays a dominant role, and approximately 44% of Harlem residents are on assisted living (NYC Planning 2017b). Air conditioners require expense not only at purchase, but also in installation, increased electrical usage, and even increases in rent (NYSHCR 2016). This may explain why residential air conditioning use in Harlem is among the lowest in the city (Kinney et al. 2011). Harlem is a historically African American neighborhood, a demographic that—for reasons that are not entirely clear—is disproportionately susceptible to heat-related illness and mortality (Madrigano et al. 2015). Nearly 50% of heat wave–related deaths in New York City between 2000 and 2011 occurred within the African American community (CDC 2013). But racial categories are correlated with the social environment, and studies in Phoenix, Arizona (Harlan et al. 2006), and Chicago, Illinois (Kalkstein et al. 1996), demonstrate the importance of social networking in diminishing susceptibility to heat stress. The combination of the physical and demographic reasons listed above and the presence of an environmental justice community action group (WE ACT; see “Introducing the partners: A science–media collaborative paradigm”) led to the selection of Harlem as an ideal choice for citizen scientist investigations into the effects of heat waves.

This study was made possible by citizen scientists energized by the realization that heat waves affect and even kill a disproportionate number of Harlem residents. To better understand the causes and solutions to these disparities, research must be embedded and ignited by the very communities struggling for health and environmental justice. Research is often conducted without community input or guidance, with the goal of advancing a discipline or system of knowledge rather than making real change in the lives of people. This may result in poor solutions to the problem at hand. The end goal of the Harlem Heat Project was to support the community in better understanding the problem of heat waves, giving residents opportunities to find their own solutions and guide policy that works for them in their neighborhoods.

Like many research-oriented community action groups, WE ACT for Environmental Justice works under the framework of community-based participatory research (CBPR), which seeks to break down the hierarchies involved in traditional scientific research by involving community members throughout the research process (Israel et al. 1998). Under a CBPR method, scientists work in close collaboration with community partners involved in all phases of the research. This ranges from defining the problem to the methodology used for researching the problem. In a CBPR model, the research findings are communicated to the broader community—including residents, media, and policy makers—in language and a manner that is respectful of participants’ contributions, to ensure that a grassroots-level experience is utilized to effect needed changes in policy.

**PROJECT DEVELOPMENT.** The idea of gauging indoor residential temperatures during a New York summer originated with AdaptNY, inspired by a workshop on measuring temperatures in the subways for a story by WNYC (www.wnyc.org/story/hottest-subway-stations-map-nyc/). AdaptNY then reached out to WE ACT for Environmental Justice, a Harlem-based community organization with past experience in citizen science campaigns. WE ACT recruited its members to host sensors and maintained the flow of data. WNYC public radio and ISeeChange joined to tell both the data-driven and human stories that arose from the research. Leveraging off a previous story on the urban heat island, WNYC recruited the scientific research team from the City University of New York. All the partners helped to design the experiment, collect data, build the sensors, and reach out to participants. These collaborators are described in the “Introducing the partners” sidebar.

The project was officially launched with an information, recruitment, and training workshop in July. It was bookended by a half-day forum in October, described in “The human side of the data” sidebar, in which the project participants shared their stories, data, and ideas with the media, academia, and members of key city agencies.
Data collection was organized in three layers. Residents were recruited mainly by WE ACT and were provided instruments to place in their homes. They were grouped by personal connection to liaisons, serving as the means of communication between the management team (the authors of this paper) and the...
residents, who frequently did not have web or e-mail access. The liaisons not only had computer access, but training in instrument placement and data upload, and further training in journal entry into the ISeeChange website or phone application (app).

**EXPERIMENT DESIGN.** Our pilot study placed temperature and humidity sensors in 30 residences of northern Manhattan, with variable reporting periods (depending on recruitment and battery life) from early July through late September of 2016 (Fig. 1). Residents were recruited via the WE ACT membership, with an emphasis on those who had no or limited air conditioning; there were no other constraints other than willingness to participate. Half the residences were in tenement buildings (5–8 stories high, narrow walkways in between, typically made of brick) dating from the first half of the twentieth century, and the remainder were from row houses (3–4 stories high, stone or brick) or large public housing apartments (greater than 15 stories high, well spaced apart with greenery, brick construction). Half of the residences did not have air conditioning; for the rest of the residences all but one of the air conditioners were in a different room from the sensor.

Sensors were hand constructed both to save money and to invite community participation, consisting of a temperature–RH sensor, battery, Micro Standard Digital (MicroSD) card, and datalogger at a total cost of about $60 per unit. Parts and construction are detailed online (at [https://github.com/datanews/harlem-heat](https://github.com/datanews/harlem-heat)). The Adafruit DHT22 sensor has a manufacturer’s quoted accuracy of 0.5°C in temperature and 5% of RH; a comparison between sensors confirmed the temperature consistency across devices. The chip could be removed for data download, with most residents e-mailing the data but some mailing alternating chips each week. At a data collection rate of every 15 min, the batteries would last approximately a month per charge. Incomplete recharges, data download errors, or instrument restart failures led to the gaps seen for some residences (Fig. 1, right).

Residents were asked to place the sensors exposed to ambient air against an interior wall that did not receive direct sunlight, preferably in a bedroom and definitely not in a kitchen or bathroom. They reported the positioning of the sensor, the floor of the building, the direction the windows faced, whether they benefited from shade, the use of fans and air conditioners, and the number of occupants.

Perhaps because of the indirect liaison system, some residents placed their sensors incorrectly (inside desks, on window sills, etc.) and many of them were unaware of which direction their windows faced. In some cases...
it was clear from the timing of peak temperatures that the reported window direction was incorrect, so it was corrected in the metadata. Such metadata failures usually came to light during the analysis portion of the project, and ways to ensure higher-quality control in such citizen scientist efforts are discussed in the “Lessons learned from the partnership’s first year” section.

Outdoor weather data were used for comparison to indoor conditions. Consistent weather data are available from the Central Park weather station (3 km from central Harlem) and the two airports: LaGuardia (10-km distance) and John F. Kennedy (20-km distance). It is not clear that adjacency makes Central Park the best representative of Harlem conditions simply because the station is surrounded by dense vegetation with different thermal properties from the neighborhoods. But since our modeling results show slight improvements using Central Park data, it is used throughout this study. Cloud cover was estimated from Geostationary Operational Environmental Satellite-East (GOES-East) geosynchronous satellite infrared imagery, by which clear and cloudy pixels were identified by spatial brightness temperature variability (Martins et al. 2002; Coakley and Baldwin 1984). Cloud fraction within each pixel (nominally 5 km apart at this latitude) was estimated by interpolation of pixel brightness temperatures between these clear and cloudy temperatures. Overcast conditions were inferred if all land pixels in the scene were at least 5°C colder than surface measurements.

RESULTS. Figure 2 shows daily weather averages during the project period. Since the project results were intended for consumption by the general public, all temperatures in this section are shown in degrees Fahrenheit. Several heat waves occurred during the project period, defined as outdoor maximum temperatures above 90°F (32°C) on consecutive days. With outdoor diurnal ranges of 12° ± 3°F (6.7° ± 1.7°C) (quoted variabilities are standard deviations), heat waves typically occur when the diurnally averaged temperatures, shown in Fig. 2, are 85°F (29°C) or higher, which occurred three times: 22–24 and 26–28 July and 11–14 August. Since indoor diurnal variations are on the order of 3° ± 1.2°F (1.7° ± 0.7°C), the daily average indoor temperatures shown approximate the indoor conditions throughout the day, with a typical 1-day lag from outdoor temperature peaks as a result of thermal inertia.

This thermal inertia can be seen more clearly by zooming in on one of the heat waves. Figure 3 portrays outdoor temperatures against a selected air-conditioned (AC) residence and two selected non-air-conditioned residences: with and without window fans. The diurnal excursions in indoor temperature are much smaller than outdoors. As the heat wave begins, the temperature of the AC residence tends

\[ \text{Fig. 2. Daily weather averages from Central Park plus indoor temperatures (°F). Outdoor temperature (red solid line) and dewpoint (blue solid lines). The indoor temperatures are averaged across the residences and are denoted by boxes: without AC (red) and with AC (in another room; blue). Wind speed (blue; mph; right axis) and rainfall events (green). Cloud cover is indicated in the upper-bar color, with bright blue for clear skies and darkening shades of blue/gray for partially cloudy to overcast conditions.} \]
to match the outdoor lows, while the temperature of each non-AC residence climbs closer to the peak each day, and the temperature of the non-AC/nonfan residence actually exceeds the outdoor temperatures. As the heat wave ends, the non-AC temperatures drop slower than outdoors, so after the heat wave these indoor temperatures are higher than outdoors throughout the entire diurnal cycle for several days. In general the warmest residences lack AC and are on the upper floors with a southern exposure, receiving direct sunlight. The seasonal average summer temperatures indoors were always warmer than outdoors, even in residences that had air conditioning.

The specific period and residences shown in Fig. 3 can be generalized into average diurnal cycles with the inclusion of all residences of sufficient sample time. Since the primary interest is health impacts, the temperatures are combined with humidity to produce the form of heat index commonly used by the National Weather Service (Steadman 1979; Rothfusz 1990), both outdoor and indoor as shown in Fig. 4. Based on a detailed physical model of a lightly clothed standard-sized person walking in the shade with a light breeze, the heat index calculates how the effects of humidity on evaporative cooling changes the apparent temperature (rate of heat transfer) in comparison to similar conditions with a dewpoint of 57°F (14°C). The average dewpoint during the observation period was 65°F (18°C), so the apparent temperature normally deviated several degrees from the actual temperature. Since indoor temperatures are relatively flat compared to

**Fig. 3.** AC vs non-AC residences during a heat wave. Outdoor temperatures are shown in black, AC indoor temperatures are in green, window fan (non-AC) temperatures are in yellow, and non-AC (no window fan) temperatures are in red.

**Fig. 4.** Average diurnal variation of heat index, indoor vs outdoor for multiple residences. Green lines indicate homes with no AC or window units in a room separate from the sensor. Blue lines indicate residences with AC in the same room as the sensor.
outdoors, and the absolute humidity typically varies little during a day, the indoor diurnal heat index also tends to be flat (Fig. 4). It is typically elevated above the outdoor average as a result of windows acting as a greenhouse. This means residents experience long-term exposure to average heat indices that are typically higher than outdoors: in our sample roughly two-thirds of the residences experience average elevated heat conditions compared to outdoors, compared to 100% of participants with higher indoor temperatures (Quinn et al. 2017). It is not known if this difference is due to random sampling effects or different selection criteria. This indoor–outdoor difference is not taken into account in most health studies that are based on outdoor conditions only. As seen in recent research, the effects of window unit air conditioning are not readily apparent (Quinn et al. 2017). The two residences with air conditioners in the same room as the sensor fell into the middle of the distribution in Fig. 4, perhaps because this average is done over the entire period rather than just during heat waves, when residents are more likely to accept the extra cost and noise of operating their units.

The thermal inertia of buildings produces both smoothing and a lag of indoor temperatures compared to outdoors, an effect captured by lag correlations. Figure 5 shows lag correlations of outdoor and average indoor temperatures, with the horizontal axis indicating the offset in time. The left panel shows the results for daily average temperatures. For each calculation a vector is formed of the daily mean temperatures averaged across all residences (the number of residences reporting each day varies, but the total is never less than 12), then offset by successive time steps to form lag correlations either with itself (autocorrelation) or with the vector of outdoor daily average temperatures. The lag autocorrelation functions for outdoor and indoor temperatures, and the lag correlation between indoors and outdoors are all plotted together. As expected the autocorrelation lag for outdoors drops off faster than indoors, but the correlation between indoor and outdoor temperatures has a shallow maximum at a 1-day lag (Smargiassi et al. 2008). When repeated for hourly temperature averages (right panel), both autocorrelations exhibit a diurnal second peak after a 24-h interval. The indoor–outdoor correlation has a first peak at a 2-h lag and the second peak is also lagged 2 h from the autocorrelation peaks, comparable to that found by Quinn et al. (2014). The difference in the daily and hourly lags can be understood by returning to Fig. 3. Because of daily variations in the diurnal wave, the hourly averages must correlate best to the same day, even if the indoor daily averages reach their heat wave peak a day later than indoors, as seen in the multiday comparison of selected residences in Fig. 3.

MODELING OF INDOOR TEMPERATURES.

In the absence of air conditioning, the indoor environment is forced entirely by the outdoor environment. It is possible to predict changes in indoor temperature by energy flows between the two systems, with adjustable constants tuned for each residence (White-Newsome et al. 2012). If there are enough data for each residence to prevent overfitting, a physical model is preferable to the simplicity of statistical models (Quinn et al. 2014, 2017) because of the ability to reproduce situations outside the sample space. Past researchers have concluded that human intervention in the form of window adjustments and fan use cause dynamic changes to thermal parameters that preclude direct physical modeling (Lomas and Porritt 2017; Coley et al. 2012); yet, if humans are consistent enough to be considered “part
of the system” on the scale of days (rather than hours), such an approach may still work. Figure 6 diagrams the physical mechanisms accounted for in preliminary modeling done for this project. Heat conduction is proportional to the difference in temperature between the residence $T_R$ and the ambient air temperature $T_a$ outside, which is the same form taken for temperature changes caused by mixing with outside air through the window. These two effects can therefore be represented by a single combined transfer coefficient. The indoor–outdoor conduction rate increases linearly with wind speed $W$. Conduction also occurs between the residence and a “storage temperature” of the more thermally massive building $T_b$, modeled as a weighted average of the last few days of the residence temperature. Solar energy $S$ is modulated by the cloud fraction (CF) broken into morning and afternoon periods as separate inputs to capture window directionality as the sun shifts, while radiant thermal energy is proportional to the fourth power of the temperature of the radiating body according to the Stephan–Boltzmann radiation equation. Since the walls of the residence are assumed to be at the internal temperature $T_w$, the only imbalance in thermal infrared radiation would be at the windows (or poorly insulated exterior walls), radiating at a temperature $T_R$ intermediate between the residence and the outside air temperature.

The temperature of the residence will change according to

$$C \frac{dT_R}{dt} = \sum_i K_i E_i$$

$$(k_1 + k_2 W) (T_a - T_R^i) + k_3 (T_R^i - T_b^i) + (k_4 CF_m + k_5 CF_a) S + k_6 (T_w - T_R^i),$$

where $C$ is the effective heat capacity, $E_i$ are the various energy flows described above matched to the parenthetical expressions, and $k_i$ are adjustable constants characteristic of each residence. The heat capacity $C$ can be absorbed into the $k_i$ constants, which are found for each residence by regression against changes in average temperature $(dT_R)$. But first the building storage temperature $T_b$ and the exterior wall/ window temperature $T_w$ must be defined.

Building storage temperatures for each residence are defined as

$$T_b = \frac{\sum w_n T_{b,n}}{\sum w_n}; \quad w_n = e^{-n/\tau}, \quad (2)$$

which is the weighted average of the last few days’ residential temperature, with exponentially decaying weights $w_n$ with decay constant $\tau$. The decay constant was provisionally set to two days, with the sum done over the previous three days. The exterior wall or window temperature $T_w$ is calculated as

$$T_w = \left[ f T_R + (1 - f) T_a \right], \quad (3)$$

where the wall temperature equals the residential temperature if $f$ is set to 1 and equals the air temperature if $f$ is set to 0. The $f$ parameter was provisionally set to 0.5. The provisional constants $\tau$ and $f$ are incorporated in a nonlinear fashion and must be found by relaxation for each residence, which was not done for this pilot study.

Given the slow rate of indoor temperature change, the time step was set to a day, with daily average temperature values. A simple anthropogenic term to account for daily adjustments of curtains, etc., was applied as a function of indoor temperature [human influence set to zero below 80°F (27°C) and rises to a maximum at 90°F (32°C)] but remains under development. Though somewhat oversimplified, a more complex model risks overfitting this 2.5-month dataset.

Except for physically obvious exceptions, such as the case where an air conditioner was in the same room as the sensor, the modeling exhibited...
considerable skill in predicting the next day’s indoor temperature, as evidenced by correlation coefficients above 0.9 between predicted and observed temperature changes with average absolute errors ranging from 0.2° to 0.6°F (0.1°–0.3°C). Despite this skill, in about one-third of the cases the coefficients in Eq. (1) were not physically consistent—conduction coefficients indicating heat flowing in the wrong direction, for example—so a deeper discussion awaits a more extensive dataset allowing further development of human adjustment functions (windows, etc.) and heat storage.

Even given these physical inconsistencies, the results from this preliminary model demonstrate two significant points worth reporting:

1) The indoor temperatures are statistically consistent enough to be predictable.
2) Even with human intervention in the form of air conditioners in other rooms, curtain adjustments, etc., the indoor air temperature remains predictable.

The results are illustrated in Fig. 7, showing modeled day-to-day changes in indoor temperature (purple) and actual temperature changes (black). The left panel with no air conditioning is as predictable as the right panel with an air conditioner in another room of the apartment. This means that when an outdoor heat wave is predicted, an indoor heat wave can be predicted concurrently. As the indoor heat wave is rather different from its outdoor cousin, and since people are typically indoors during these events, indoor prediction is arguably more impactful. A fully physical model with parameterized human adjustments may allow indoor forecasts several days in advance.

LESSONS LEARNED FROM THE PARTNERSHIP’S FIRST YEAR. The partnership between media, community groups, and scientists is novel enough to bring some of its own challenges, calling for organization a step beyond the normal collaboration. Below are some of the lessons we learned while working together that may be useful to others.

Human management and communication. Diverse partners require additional advance planning. Media, community, and research organizations all work at different rates, so timetables must be worked out with all partners far in advance. In our case, a springtime initiation for a late-summer project was barely adequate, creating avoidable push and pull between the moving parts.

Community organizing requires funding for dedicated staff. This project was run without dedicated funding, so time and tasks had to be shared among several people taking time off from other funded projects. The community organization in particular required more time than anticipated to manage lightly trained volunteers working with unfamiliar instrumentation and software. Funding should be planned for a full-time community focused staff member during the active period of any similar project.

Plan internal communications. A dedicated communication portal [in our case, the Slack app (www.slack.com)] is essential for keeping the management synchronized from the beginning. Deciding on the means of communication and file sharing should be among the first management decisions made, providing a dedicated channel separating the project from other forms of communication.

Fig. 7. Observed changes in indoor air temperature from one day to the next (black) vs modeled changes in temperature (purple). (left) Residence has no air conditioning, and (right) residence has an air conditioner in different room than the sensor.
**Personalize communication with participants.** Via the community organization we had a layer of liaisons between project management and participating residents, a system based on personal connections. Though a somewhat rushed implementation caused some issues with training, we feel this approach is an important way to reach at-risk populations. The liaisons spent time going door to door to check in and follow up with the residents: the level of engagement and trust the community organization brought to the work was essential for its success. If we had relied on the data alone, we would have missed much of the narrative context, deeper questions, and opportunities to improve outcomes. Being present matters.

**Provide a range of interface options.** Multiple opportunities for residents to participate is essential. Most residents use their cell phones—mainly Androids—for Internet access. Therefore, both computer and cell phone portals are required for reporting. In the case of residents with neither a computer nor a cell phone, we deputized engagement reporters and neighbors (liaisons) to report experiences on their behalf. Providing paper journals would have been a more accessible option. Given the range of access and comfort with technology, it is best to plan ahead to ensure participant reporting is inclusive.

**Provide deep training for participants.** We hosted a single training session on sensor use and experiential reporting (through ISeeChange) during the project launch, targeted primarily at the liaisons (see above), who would in turn train the other participants. This proved insufficient, and many residents were unable to report by themselves or placed sensors in kitchens, inside desks, etc. Either extended or repeat training is required, with built-in checks during the experiment to ensure the information is properly assimilated out in the field. Alternatively, a small cadre of specially trained team members should visit all participants during the launch of the measurement campaign.

**Provide for language and conceptual barriers.** Several participants did not speak English. Though we could address this through the liaisons, it would have helped if guide sheets and Internet portals had been translated. Even so, conceptual barriers existed. For example, many residents did not know which direction their windows faced: crucial for understanding the role of sunlight on indoor temperatures. Such unexpected blind spots can be caught only by testing with the target population.

**Be aware of social constraints.** Hesitation or even embarrassment about not being able to afford an air conditioner demands that project partners respect the dignity of the participants and their homes. In some cases, anonymity was requested for those secretly maintaining air conditioners in public housing to avoid added unaffordable fees from housing authorities. The option for anonymous reporting is needed.

**Instruments and data management.** Create a dedicated data portal. A central management space should be created for tracking the ins and outs of the data, not just data storage. This should be on an independent website/portal so that it is not tied to any one group’s security. We had data storage, data flow tracking, and device metadata (description of residence attributes and sensor placement) handled by three different people on three different sites, creating unnecessary hindrances. It worked because the project was relatively small. Creation or purchase of a data management application early in the planning process is recommended.

**Favor real-time retrieval over episodic data retrieval.** We used weekly data retrieval partly because there was less initial setup required and partly because it might lead to tighter interaction with the community. But real-time retrieval is by necessity automated, and we found the drawbacks of depending on the vagaries of participant-level data upload outweighed the benefits. Not only does real-time retrieval streamline the data collection process, but it also allows participants to become immediately engaged in the data they are producing. We missed many opportunities for documenting the human impacts simply because the data were delayed by design.

**Design for individual sensor discussion.** A separate channel for each liaison to discuss the sensors under her care is ideal for purposes of clarity. We had one channel under which all sensors were discussed, producing a tangled flow of logic. Even separate threads would work, but the protocol must be clearly established during the planning phase.

**FUTURE PLANS: A TOOL FOR HEAT-RELATED SOCIAL NETWORKING?** Based on our preliminary results we can envision a system of indoor sensors reporting real-time data and short-term forecasts via an online portal. The reporting would have anonymous identifiers so residents can track their own temperatures and predictions, but the ensemble of results would be available to all. City
health and emergency management officials could use the ensemble of indoor temperature forecasts as a warning system to augment those based on outdoor weather prediction, while researchers would benefit from the automated dataset. But would such a system have an impact?

Research on state housing in Great Britain suggested that “soft” human interventions such as window and fan usage were as important as “hard” interventions in the form of housing construction (Coley et al. 2012; Lomas and Porritt 2017), while recent research shows that New Yorkers rarely make window adjustments even when it would lead to cooler indoor conditions (Quinn et al. 2017). It seems intuitively plausible that if residents were provided with real-time reminders that conditions were amenable to improvement by simple behaviors, such as turning on fans or pulling shades, they may be more inclined to do so. But a more difficult goal would focus on social interactions that have been shown in Philadelphia, Pennsylvania, and Chicago, Illinois, to be crucial to preventing heat-related deaths (Kalkstein et al. 1996; Palecki et al. 2001). Based on these experiences, New York City has launched its Cool Neighborhoods initiative, featuring the Be a Buddy program, in which residents will check on each other during heat waves, and will host workshops with media and community groups to improve communication during heat waves (NYC Mayor’s Office 2017). It is not yet clear how these plans will be implemented, but a system of real-time reporting of residential conditions dovetails with these initiatives and could significantly strengthen them.

Implementing real-time sensing in vulnerable residences is not an easy task, since residents are unlikely to have Internet connections except through mobile devices. Building on the experiences of the HeatSeek project (www.heatseek.org), we plan to implement Low Power Radio Wide Area Network (LoRaWAN) technology, by which sensors radio their data to central receiving antennas, bypassing the need to install Wi-Fi base stations for each building. These receiving antennas are public access if set up via The Things Network system (www.thethingsnetwork.org), routing data from registered sensors to servers for real-time retrieval by any project. This ability for multiple projects to piggyback off the infrastructure has motivated the borough of Manhattan to support and partially fund a system of these antennas. Because of building interference, the practical receiving radius of these antennas is 2–3 km, and we estimate Manhattan could be covered by approximately 20 antennas as a public data transfer backbone for sensor networks. Manhattan’s model may encourage other municipalities to do the same.

**CONCLUSIONS.** The Harlem Heat Project was a unique collaboration between media, community, and scientists that documented the human impact of indoor heat waves. The comparison between outdoor and indoor heat waves indicates a need to change the warning and classification systems to better serve the public. In the absence of air-conditioning (or even with light use of it), indoor heat waves are smoothed and lagged a day or so compared to outdoor heat waves because of thermal inertia of residences and are often elevated by the greenhouse effect of windows. The indoor conditions can be predicted separately for each residence based on outdoor conditions. The city agencies present at the culminating workshop of the project saw definite value in the work, and we hope to assist them by building an indoor weather/forecast system around a network of real-time residential sensors. Such a system may assist in building the social structures needed to address the effects of heat stress.

Natural crises, such as heat waves, are often portrayed through facts and diagrams in a way that does not always engage the public. Storytelling has the capacity to build empathy and understanding of the problem of environmental injustice on an individual level. In New York City, we were able to tell a different—and, we would argue, new—side of the story when it comes to heat waves: the disparity in how people experience these episodes within their homes. Listeners from across the city heard personal stories about health issues, coping mechanisms, and access to cool spaces that people in their community were facing—people they could relate to as neighbors. The stories made the often invisible problem visible.

If other researchers plan to enter the world of citizen science, we hope this article suggests new opportunities for science in the public interest. Media involvement spurs community involvement. It is a new community-engagement model for doing science.

**ACKNOWLEDGMENTS.** This work was supported by NOAA/EPP Grant NA11SEC4810004 to the CREST Institute at the City University of New York, a joint Professional Staff Congress and City University of New York (PSC-CUNY) award to AdaptNY, a grant from the Kresge Foundation to WE ACT for Environmental Justice, and a grant from the Wyncote Foundation’s New Enterprise Fund
to iSeeChange. We greatly acknowledge the NCDC data tools for access to archived weather data. Reviewer input was substantive and deeply appreciated.

REFERENCES


Rothfusz, L. P., 1990: The heat index “equation” (or, more than you ever wanted to know about heat index). NWS Western Region Tech. Attachment 90-24, 3 pp., www.weather.gov/media/wrh/online_publications/TAs/ta9024.pdf.