Modeling Occupant Core Temperatures Across the Boston Building Stock to Advance Public Health and Utility Efficiency

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ABSTRACT

In recent history, extreme heat has been the cause of most deaths from a natural disaster. Exposure to extreme heat can aggravate preexisting conditions, increase hospitalization, and even cause death. Thus, modeling the thermal resilience of households across the United States will allow for a quantitative assessment of the health and safety risks posed by extreme heat. For the first time, we simulate occupant comfort in representative households across Boston by combining the granular results of the ResStock™ model with a two-node heat strain model. This model calculates occupants' core body temperature in each simulated household over a year. We compare the simulated core temperatures to two public health metrics: hyperthermia and heat stroke. Our results show for households in Boston that do not have or use aid conditioning, thousands potentially experience many dangerous heat events each summer and these events can last for more than a day at a time. These heat events peak during the late afternoon and evening, just as residents are coming home, cooking meals, and trying to go to sleep. We have found that multi-family buildings, renters, and low-income homes in more airtight and insulated homes are the most at risk for these events. These results demonstrate the scale and urgency of exposure to extreme heat.

Introduction

According to the National Weather Service, between 2013 and 2023 extreme heat was the most common weather-related event resulting in acute death in the United States, causing over 36% of weather-related deaths ("Weather Related Fatality and Injury Statistics," n.d.). In a heat wave in St. Louis and Kansas City in 1980, about 1 in every 1,000 residents was hospitalized or died of heat-related illness (Jones et al. 1982). In 1995, a heat wave in Chicago caused 600 excess deaths and 3,300 excess emergency department visits for near-fatal heat stroke (Dematte et al. 1998). Over the course of the summer of 2003, heat waves in England, Wales, Italy, France, Portugal, Spain, and the Netherlands caused an estimated 33,500 to 37,500 deaths (Kosatsky 2005).

Beyond morbidity, exposure to extreme heat has serious health consequences. Exposure to extreme heat can impact even the most healthy individual by causing heat-related illness such as heat cramps, heat exhaustion, and in the most severe cases, heat stroke (Fraser et al. 2017). Extreme heat can exacerbate conditions like cardiovascular and respiratory diseases and can lead to consequences like hospitalization, increased medical bills, or even premature death (Berko 2014; Luber and McGeehin 2008). Beyond acute health issues, higher indoor air temperature can lower productivity and has been shown to increase medical care costs and the use of sick leave (Flouris et al. 2018; Seppänen and Fisk 2005).

From a public health perspective, all heat-related illnesses are preventable, thus so too are all these issues. For residents, fewer trips to the hospital or emergency room for heat-related illness would save them money. Additionally, lower heat stress would result in fewer co-morbidities that are exacerbated by exposure to extreme heat, further lowering healthcare costs (Ai et al., 2026). Fewer trips to the hospital would also lower the strain on the healthcare system, increasing staff retention, improving outcomes for other patients, resulting in lower healthcare costs for citizens generally (Bar-Yam, 2006). Thus, an investment in improving the indoor conditions for vulnerable households will benefit all residents by eliminating the time, energy, and costs associated with these heat-related illness.

Hyperthermia and heat stroke are two common public health metrics that are used to quantify exposure to extreme heat. Hyperthermia can cause acute cognitive dysfunction, including adverse effects on attention (Sun et al. 2012), memory (Racinais et al. 2008), and information processing (Sun et al. 2011). Sustained exposure to extreme heat can lead to cardiac ischemia, infarction, and congestive heart failure (Boyette and Manna 2023; Zanobetti et al. 2012). The risks associated with heat stroke are even greater. When a human's core temperature exceeds 104°F, they experience central nervous dysfunction, including combativeness, delirium, seizures, and coma, along with the possibility of multiple organ failure (Leon and Bouchama 2015; Epstein Yoram and Yanovich Ran 2019). In the medical literature, the mortality rate for patients who experience heat stroke ranges from 10% to 65% and was greater than 50% for the elderly (Bouchama and Knochel, n.d.). More than 80% and 70% of patients in studies experienced some level neurological and cardiovascular damage, respectively (Adnan Bukhari 2023). For those that survive, studies show that more than 75% will have a functional impairment of varying severity (Leon and Bouchama 2015).

Many metrics and models have been developed to understand how the human body responds to a changing environment to determine comfortable living and working conditions inside buildings. These metrics and models can be generally classified into three groups: heat stress metrics, heat strain models, and thermal comfort models (Figure 1). Heat stress metrics evaluate the net heat load on a human body and are calculated using only environmental and occupant parameters (Siu et al. 2025; Havenith and Fiala 2015). Their simplicity allows them to be quickly and easily disseminated to and comprehended by the general population (e.g., heat index in a news weather report). The next two types, heat strain models and thermal comfort models, increase the responsiveness to occupant comfort by calculating the physiological response of an occupant (Siu et al. 2025; Havenith and Fiala 2015). These models simulate how a typical human body would respond to changes in temperature (i.e., sweating and shivering). Thus, they require highly resolved timeseries data to accurately model indoor conditions for an occupant (Siu et al. 2025). Moreover, each household and occupant would need to be considered individually, further reducing the generalizability of these models. Thermal comfort models distinguish themselves from heat strain models by accounting for an occupant's subjective perception of their own comfort (Siu et al. 2025; Katić et al. 2016). Adding another layer of complexity, these models are the least generalizable across a large population or building stock.

While all three metrics and models outlined in Figure 1 provide useful information, heat strain models are the best for addressing the impacts of extreme heat. Heat stress metrics can easily warn residents of the possibility of dangerous conditions. However, they lack the granularity to indicate which specific households are in the most danger from extreme conditions

(Siu et al. 2025). Furthermore, residents cannot use these metrics to determine ways to retrofit their households that will prevent dangerous conditions in the future. Likewise, thermal comfort models are equally ill-equipped to prevent the impacts of extreme heat. The primary use case of these models is to tune occupant comfort rather than to detect dangerous conditions (Kenny et al. 2019; O'Connor et al. 2024). These models focus on steady-state conditions where heating and cooling systems are actively responding to changes in outdoor conditions and occupant needs (Siu et al. 2025). These models are not meant for situations where the HVAC cannot operate (e.g., power outage) or for households without cooling (Katić et al. 2016; Ole Fanger and Toftum 2002). Heat strain models provide the granularity to address the unique situation and needs of individual residents while focusing on the physiological response to extreme heat rather than relying on a subjective perception. However, given the input data requirements of heat strain models, previous studies have only focused on individual households or basic archetypes (Siu et al. 2025; Jakubiec 2022).

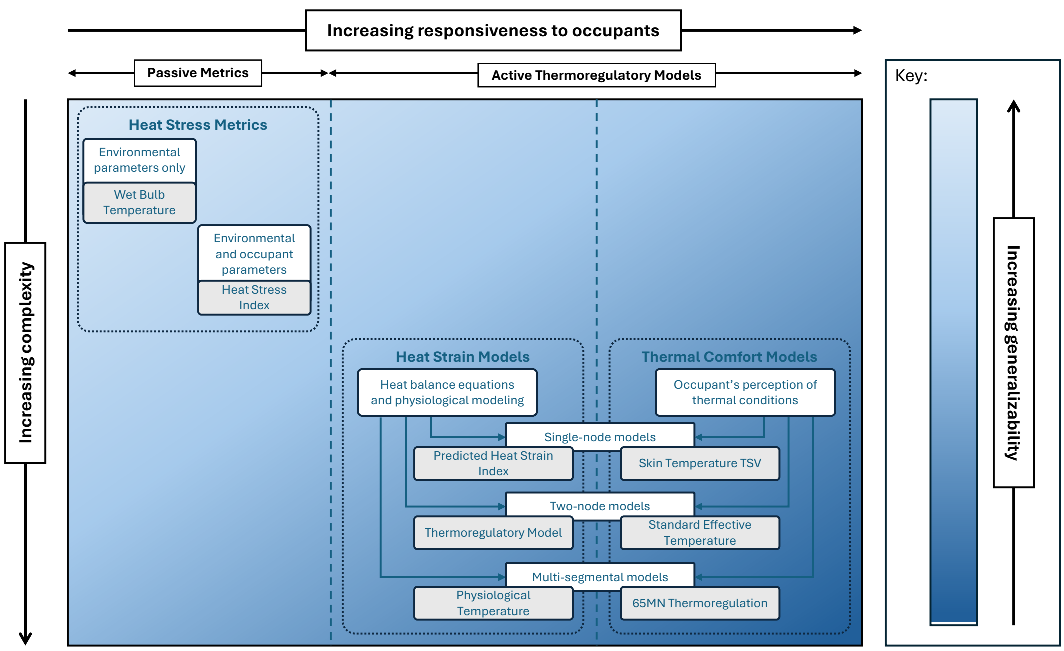

Figure 1: Types of metrics and models to evaluate heat-related health risks with examples.

In this study, we leverage first-of-its-kind building stock time-series data in the application of a heat strain model to understand the public health implications of extreme heat. Leveraging household characteristic and timeseries data of indoor conditions from the latest standard data release of the ResStock^{TM} model, we can model occupant core temperatures. We correlate the core temperatures with public health metrics to understand the impact on human health of households without cooling in the greater Boston area.[1] For the rest of the article, we

[1] We define the greater Boston area as the Boston-Worcester-Providence, MA-RI-NH core-based statistical area as defined by the U.S. Census Bureau.

will refer to this area as simply Boston. In doing so, we can answer the following research questions:

1. How many households are experiencing dangerous indoor conditions? Additionally, based on households that have but do not use cooling, how many more households experience dangerous indoor conditions?
2. What are the most effective actions occupants can take to mitigate the impacts of dangerous indoor conditions?
3. For households that experience these dangerous indoor conditions, how many times during the summer do occupants experience these conditions and for how long do these conditions persist?
4. What are the characteristics of households experiencing dangerous indoor conditions?
5. When, in terms of time of day, do households experience dangerous indoor conditions?

Methodology

We developed a four-part methodology to determine dangerous indoor conditions in residential households in Boston. First, we queried timeseries data of indoor conditions from building models in Boston from the ResStock model. To match field data from an experiment in Boston, an adjustment is made to the relative humidity timeseries data. Second, we defined a thermoregulatory model and its inputs to determine an occupant's core temperature. Third, we defined the public health metrics that are used to identify dangerous indoor conditions based on occupant core temperature. The adjusted timeseries data was fed into a thermoregulatory model that output timeseries data of occupant core temperature. This timeseries data was compared with the public health metrics to determine if dangerous indoor conditions exist (Figure 1). Last, we conducted a sensitivity analysis on the primary assumptions from the thermoregulatory model to understand the limitations of the model and gain insight into heat strain-limiting behaviors, defined as behaviors that limit the impact of extreme heat, and their effectiveness.

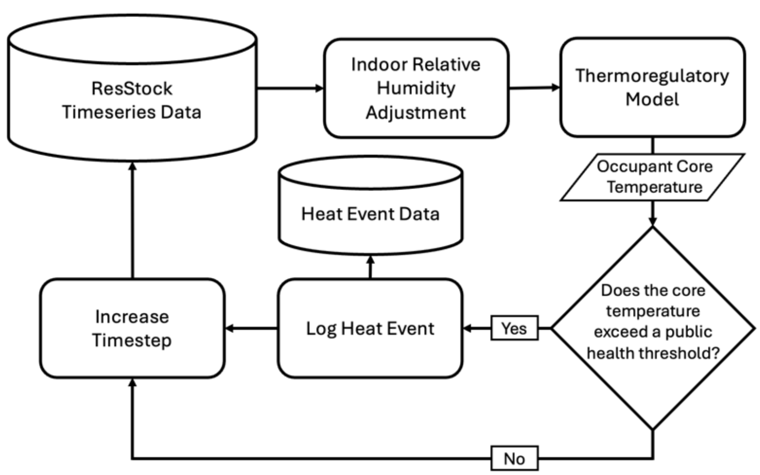

Figure 2: Flowchart illustrating the major processes to identify heat events that cause dangerous indoor conditions.

ResStock Model Data

To overcome the data availability limitation associated with heat strain models, we leveraged the most recent standard data release from the ResStock model ("ResStock - NLR" 2025). ResStock is a bottom-up, physics-based building stock energy model developed by the National Laboratory of the Rockies (formerly the National Renewable Energy Laboratory) (Wilson et al. 2017). The most recent ResStock standard data release (2025.1) uses 11 national and regional data sources to define the relative probability of over 200 residential building characteristics of ~550,000 representative residential households through a set of conditional probability tables. Using the OS-HPXML workflow, ResStock calculates and reports the sub-hourly energy consumption and indoor condition timeseries data of each of these households models for an entire year using 2018 actual meteorological year weather data ("ResStock - NLR," n.d.). We queried the indoor air temperature, indoor mean radiant temperature, indoor humidity ratio, and indoor relative humidity timeseries data for all households without cooling in Boston.

In a review of the timeseries data, the reported indoor relative humidity of households without cooling seemed significantly different compared the outdoor relative humidity. Two studies measured the indoor and outdoor relative humidity in households throughout Boston and found that while indoor relative humidity was offset from outdoor relative humidity, the difference was not as great as that reported in the EnergyPlus® calculations that underpin this ResStock data (J. L. Nguyen et al. 2014; Jennifer L. Nguyen and Dockery 2016). Therefore, we implemented a modification to indoor relative humidity timeseries data given that this variable has such a large impact on the heat strain model. Using measured field data from 16 households in Boston, Nguyen et al. calculated the regression coefficients to calculate indoor relative humidity based on the outdoor relative humidity (J. L. Nguyen et al. 2014). Equation 1 uses those regression coefficients to calculate an adjusted indoor relative humidity for this study.

Equation 1

$$RH_{indoor,adjusted} = 17 + (0.45 * RH_{outdoor})$$

where *RH* is relative humidity.

To ensure the energy content within the indoor air remained the same through this transformation, we calculated the enthalpy of the indoor air at its originally calculated humidity ratio (Equation 2).

Equation 2

$$h = c_{p,air} * T_{indoor} + X * (L_v + c_{p,water\ vapor} * T_{indoor})$$

where *h* is enthalpy [kJ/kg], c_p is the specific heat capacity of air [kJ/kg*°C], *T* is air temperature [°C], *X* is the humidity ratio [$kg_{water}/kg_{dry\ air}$], and L_v is the latent heat of vaporization [kJ/kg].

Using the CoolProp python library, which leverages psychrometric relationships, we calculated an adjusted dry bulb temperature based the adjusted indoor relative humidity (from Equation 1) and the enthalpy of the original indoor air conditions (from Equation 2) (Bell et al. 2014). The adjusted dry bulb temperature and relative humidity timeseries data, with the same enthalpy as the original indoor air is then fed into the thermoregulatory model along with the original indoor mean radiant temperature data.

Thermoregulatory Model

We used the Pierce two-node model of human thermoregulation to calculate changes in an occupant's skin and core temperature in response to changing indoor conditions. The foundation of this model is the basic heat balance equation of the human body where the rate of heat stored in the body is equal to the metabolic heat production minus the heat lost to the surrounding environment through evaporative, convective, and radiant heat transfer from the occupant (Fanger 1970). The Pierce model adds an additional layer of complexity to this basic heat balance equation by using a finite difference procedure to represent the human body as two concentric cylinders (i.e., nodes) (Doherty and Arens 1988). The inner cylinder represents the body's core while the outer cylinder represents the skin shell. In this way, heat storage occurs in both the skin (S_{skin}) and the core (S_{core}) compartments with heat transfer between the skin and core compartments ($q_{skin\text{-}core}$), as shown in Equation 3 and Equation 4, respectively.

Equation 3
$$S_{skin} = q_{skin-core} - R_{skin} - C_{skin} - E_{skin}$$

Equation 4
$$S_{core} = M - W - E_{core} - C_{core} - q_{skin-core}$$

where S is stored heat in the nodes, q is heat transfer between the skin and core nodes, R is radiative heat gain/loss, C is convective heat gain/loss, E is evaporative heat gain/loss, M is metabolic heat production, and W is mechanical work. All terms have the units [W/m^2].

This heat transfer between the two nodes is a function of the blood flow rate to the skin and the difference in temperatures between the skin and core (Equation 5). In Equation 5, if the temperature of the core compartment is greater than that of the skin compartment, the heat transfer variable ($q_{sk\text{-}cr}$) is positive as heat moves from the core to the skin. However, if the temperature of the skin compartment is greater than that of the core, $q_{sk\text{-}cr}$ will be negative and heat will transfer from the skin to the core, increasing the core temperature.

Equation 5
$$q_{skin-core} = (k + c_b * Q_{skin-core})(T_{core} - T_{skin})$$

where k is the thermal conductance of the human body [W/(m^2 ∗°C)], c_b is the volumetric heat capacity of blood [(W∗h)/(L∗°C))], and Q is the blood flow rate [L/(m^2∗hr].

For the purpose of this study, we examined extreme indoor temperatures that cause increases to the skin temperature that lead to an increase in the core temperature. At each time step, based on indoor conditions, the temperatures of the skin and core compartments are updated based on their temperatures in the previous time step along with the amount of heat stored in each compartment (Equation 6 and Equation 7). In this way, we can monitor the occupant's core temperature to determine if unsafe conditions arise.

Equation 6
$$T_{skin,i+1} = T_{skin,i} + (S_{skin} * A_D)/(0.97 * \alpha * m)$$

Equation 7 $$T_{core,i+1} = T_{core,i} + (S_{core} * A_D)/(0.97 * (1 - \alpha) * m)$$

where A_D is the body surface area calculated by the Dubois equation [m^2], α is the fraction of total body mass attributed to the skin compartment, and m is the mass of the body[kg].

While this model matches well with the available data, there are still many limitations to this approach. First, we chose to model the body composition and thermoregulatory characteristics of a typical healthy male adult. Occupants that are elderly, pediatric, obese, or have preexisting conditions will all be more susceptible to heat-related illnesses (Schmeltz et al. 2016; Wheeler et al. 2013). Given the complexity of physiological interactions, we did not attempt to model any of these vulnerable populations. Second, the model includes many assumptions regarding indoor conditions. We assumed the occupant is wearing light office clothing, they are doing light office work, and they are experiencing an air velocity of 0.2 m/s. Each of these conditions were subjected to a sensitivity analysis, which is described below.

Public Health Metrics

For this analysis, we identified two public health metrics that can be used to gauge dangerous indoor conditions—hyperthermia and heat stroke. Definitions of hyperthermia vary across the medical literature. Niven and Laupland 2016 defined the threshold for hyperthermia as the point when an occupant's core temperature rises of above 100.4°F. Unlike hyperthermia, heat stroke is well defined in the medical literature as the point when an occupant's core temperature rises above 104°F (Bouchama and Knochel, n.d.). Using these definitions, we have defined the lower range of dangerous occupant core temperature as between 100.4°F and 104°F, and the higher range of dangerous occupant core temperature as above 104°F. We will refer to these ranges as the hyperthermia and heat stroke thresholds, respectively.

Sensitivity Analysis

Despite the high granularity of data from the ResStock model, there are still quite a few assumed input values for the thermoregulatory model that need to be analyzed for model sensitivity. For this study, we focused the sensitivity analysis on the assumptions that pertain to the decisions that the occupant can make during an extreme heat event to mitigate an increase in core temperature (Table 1). The first assumption we made was that the metabolic heat production of the occupant corresponded with "easy office work." For the sensitivity analysis we decreased this value to the lowest possible level, which corresponds to "resting" activity according to ISO Standard 8996 (ISO 2004). The second assumption we made was that the occupant would have a standard clothing ensemble of a shirt, trousers, undergarments, and shoes based on ISO Standard 9920 (International Organization for Standardization 2007). For the sensitivity analysis we modeled the occupant as having no thermal resistance to clothing (i.e., nude) across their entire body (Havenith et al. 2015). The final assumption we made was an air velocity of 0.2 m/s, which affects the convective heat transfer coefficient (h_c) experienced by the occupant. Studies show that the upper limit for air velocity tolerance is 0.8 m/s, which is associated with a 225% increase in h_c (Mitchell 1974).

Table 1: Sensitivity analysis variable summary

Variable	Heat Balance Equation Variable	Baseline Value	Sensitivity Analysis
Metabolic heat production (W)	Metabolic heat production (*W*)	65 W/m^2	55 W/m^2
Thermal resistance of clothing (R_{cl})	Evaporative heat loss from skin (E_{skin})	0.115 m^2·K/W	0.01 m^2·K/W
Clothing area factor (f_{cl})	Radiative (R_{skin}) and convective (C_{skin}) heat loss from skin	1.14	1
Convective heat transfer coefficient (h_c)	Evaporative (E_{skin}) and convective (C_{skin}) heat loss from skin	3.1	6.975

Results

How many households are being impacted by heat events?

There are thousands of households in Boston that do not have access to cooling and that experience conditions in which an occupant could suffer exposure to extreme heat (Table 2). To answer research question 1, under baseline conditions, approximately 4,900 and 1,700 households hit the hyperthermia and heat stroke thresholds, respectively, at least once during the 2018 summer. To answer research question 2, these numbers can be decreased significantly (1,000 and 260, respectively) if residents cool with a fan, reduce clothing levels, and lower activity levels (ordered from most effective to least effective). While these mitigating activities combined result in the lowest occurrence of both the hyperthermia and heat stroke thresholds, their effects are not purely additive. Additionally, if we consider households that have but do not use cooling, according to the 2020 Residential Energy Consumption Survey, the number of households in Boston that experience these heat events could increase by ~20% ("Residential Energy Consumption Survey (RECS)," n.d.).

Table 2: Percentage of households without cooling that and estimated number of households that experience the different heat events under the baseline and sensitivity analyses conditions

	Hyperthermia Threshold					Heat Stroke Threshold				
Percentage of households that hit the threshold	2.1%	2.1%	2.0%	0.53%	0.43%	0.74%	0.74%	0.74%	0.11%	0.11%
Estimated affected households in Boston	4,900	4,900	4,700	1,200	1,000	1,700	1,700	1,700	260	260
Sensitivity analysis type	Baseline	Activity	Clothing	Fanning	All SA Combined	Baseline	Activity	Clothing	Fanning	All SA Combined

How often and to what extent are households are being impacted by heat events?

Most households that exceed the heat-related illness thresholds exceed these thresholds for hours on end, repeatedly throughout the summer (Table 3). To answer research question 3, under baseline conditions, half the households that experience conditions that could induce hyperthermia record an estimated eight of these events a year. For those households that experience conditions that could induce heat stroke, the number is more than five times a year.

Furthermore, more than 50% of the households where these hyperthermia- and heat stroke-inducing events occur, these conditions last for more than a day at a time.

Table 3: Percentile breakdown of the count and duration of heat-related events for households that experience dangerous heat conditions

	Count		***Duration (Hours)***	
Percentile	*Hyperthermia Threshold*	*Heat Stroke Threshold*	*Hyperthermia Threshold*	*Heat Stroke Threshold*
75th	11.0	8.5	39.0	64.0
50th	8.0	5.1	29.0	37.0
25th	2.5	1.5	5.0	9.7

Who is being impacted by heat events?

Figure 3 shows occupant and building characteristics of households in Boston that did and did not experience a heat event, allowing us to answer research question 4.

Figure 3: Building and resident characteristics for households that experienced dangerous indoor conditions related to extreme heat compared to those that did not experience these conditions

Dangerous indoor conditions occur more frequently in multifamily households (particularly high-rise buildings), households occupied by renters, and households with lower-income residents. This aligns with previous research that identifies these vulnerable household types (N. T. Sandoval 2024; N. Sandoval et al. 2024, 2025). One unexpected result was that dangerous indoor conditions were found more frequently in newer household (post-1990s), compared to older households. Our hypothesis is that newer households tend to be more insulated and better air-sealed compared to older households. The data in Figure 3 confirms this by showing that all the households that experience heat stroke threshold events were relatively airtight and all had infiltration values of less than or equal to 25 ACH50. Households with higher R-values for wall, floor, and ceiling insulation also experienced more occurrences of heat events. Therefore, weatherization measures that do not include adding cooling to a household, are not sufficient to avoid these heat events. In fact, these measures could make the situation worse.

When are heat events occurring?

To answer research question 5, for households that experience a heat event, most experience the event from 5 p.m. to 2 a.m. (Figure 4 and Figure 5). Given the insulation and infiltration characteristics of the households whose occupants experience heat events, the most extreme indoor conditions lag a few hours compared with the most extreme outdoor conditions.

This time frame is when occupants may be at home cooking dinner, doing chores/homework, and sleeping. If occupants in these households are forced to engage in heat strain-limiting behavior or leave their households to seek a cooling center, their typical evening activities could be impeded, which could result in economic, emotional, and physical repercussions.

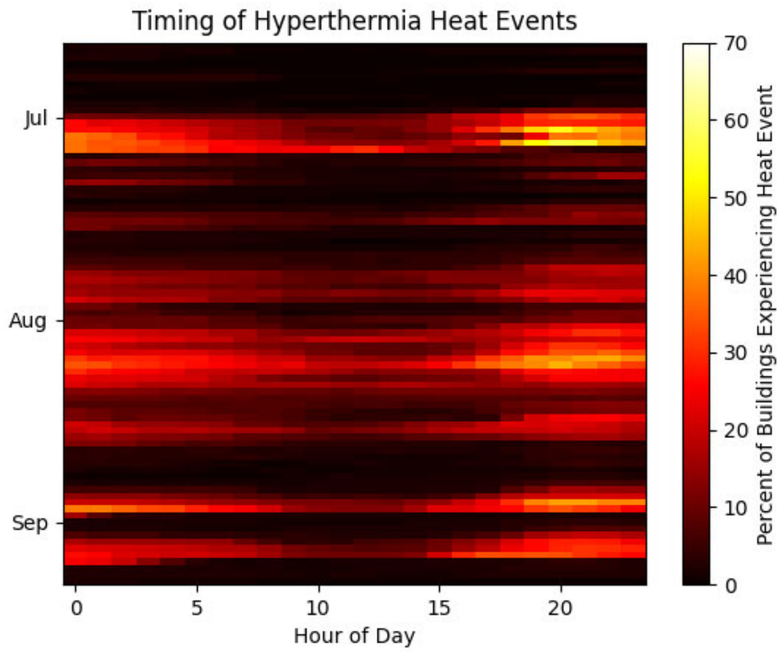

Figure 4: Heatmap of hyperthermia heat event timing (Note: Each row represents a day)

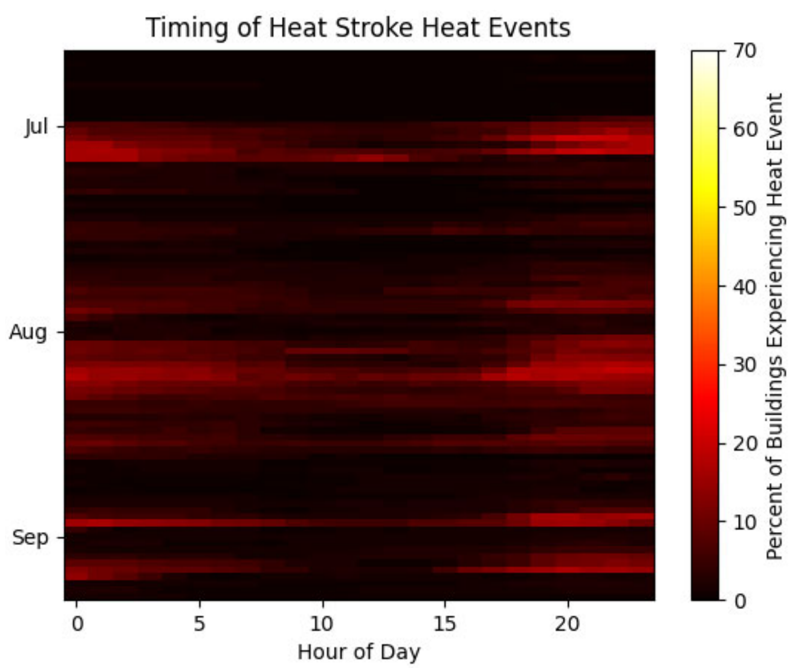

Figure 5: Heatmap of heat stroke heat event timing (Note: Each row represents a day)

Discussion

These research findings have a broad range of implications. To contextualize their import, we must address three questions. The first question is "Are these findings valid?" While the application of building stock modeling data to estimate the core body temperature of an occupant is novel and possibly transformative approach to this issue, we must first validate these findings as they do not directly estimate health outcomes from extreme heat. While not included in this publication, we are currently comparing the timing of these heat events with hospital admissions data from the Center for Health Information and Analysis in Massachusetts. To do this, we will calculate two metrics for each day. First, using the baseline results, we will calculate the percentage of households in our sample that experienced a heat event. Second, we will calculate the number of heat-related illness recorded in the hospital admissions day for that day and the subsequent three days (Ye et al. 2011). We will then use a distributed lag non-linear model (DLNM) compare the two metrics to determine if the heat events predicted in the baseline model correspond with hospital admission data using a Poisson regression. We will use a DLNM to account for both the temporal lag between a heat event and the delayed hospital admission and the fact that temperature impacts are non-linear – in extreme conditions the risk of a heat event rises sharply. While this quantitative validation will begin to help answer this question, we hypothesize that most residents are not passively sitting in their households during these extreme conditions as our model simulates. Thus, to further validate these findings, we plan on surveying Boston residents to better quantify the impact extreme heat has on their lives. In addition to validating these findings, this future work will begin to understand heat strain-limiting behaviors—similar to energy-limiting behavior—that may be creating negative impacts on these residents (Cong et al. 2024; Huang and Nock 2024). We hope to answer questions such as (1) what else are residents doing in their households to mitigate these conditions? (2) If they cannot mitigate these conditions, are they choosing to leave their households? (3) If so, where are they going? (4) What other financial and psychological impacts are these actions having on these residents? Answering any of these questions will help better quantify any co-benefits of mitigating these dangerous conditions.

The second question we must consider is "What can we do if we are correct?" In the short term, residents can immediately implement solutions such as ceiling and box fans, shades, and natural ventilation strategies to cool their households. These are feasible solutions for renters and low-income households who are some of the most prevalent groups of vulnerable occupants. For those with the financial resources, installing and utilizing cooling technologies has been shown to be the most effective strategy to immediately reduce heat strain (Luber and McGeehin 2008; Bouchama Abderrezak and Knochel James P., n.d.). At the municipality level, active measures such as the deployment of cooling centers (e.g., schools, libraries) have been shown to be an effective strategy to prevent heat-related health impacts (Kar et al. 2025). However, governments could go one step further by deploying mobile cooling centers or loaning portable cooling equipment for those with mobility issues (López et al. 2021). Passive measures such as infrastructure changes to incorporate more vegetation and water features have been shown to lower heat stress and energy consumption (Shahmohamadi et al. 2010). These measures along with the large scale deployment of indoor temperature sensors and resident engagement surveys could help to better understand the scale and characteristics of this issue.

The final question to consider is “What are the consequences if we do something about this issue?” While access to and use of cooling is the most effective strategy to reduce the impact of extreme heat, one consequence of this could be increased stress on the grid in the times where the grid is most strained. If the grid is not prepared for this increase in consumption, it could result in outages, which would only exacerbate this issue (Ai et al., 2026). Along with this, in Massachusetts alone, demand for data center capacity is projected to increase by approximately 300 MW. This will also increase the strain on the grid and might increase the cost of electricity. Additionally, waste heat from these facilities could exacerbate urban heat island effects. Integrating our findings with data center location data can be leveraged by utilities for capacity planning and demand response programs to shift cooling loads during extreme heat.

These research findings can benefit multiple stakeholders. Occupants and city planners can implement mitigation and adaptation strategies, such as retrofitting households and investing in infrastructure that reduce heat impacts and improve quality of life. Governments can leverage these data to identify households at higher risk of heat exposure and occupants most susceptible to heat-related illnesses. These insights can inform retrofitting strategies to ensure energy reliability and affordability during extreme heat event.

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