Vulnerability of U.S. Residential Building Stock to Heat: Status Quo, Trends, Mitigation Strategies, and the Role of Energy Efficiency

by

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ABSTRACT

Thermal extremes are responsible for more than 90% of all weather-related deaths in the United States, with heat alone accounting for an annual death toll of 618. With the combination of global warming and urban expansion, cities are becoming hotter and the threat to the well-being of citizens in urban areas is growing. Because people in modern societies (and in particular, vulnerable groups such as the elderly) spend most of their time inside their home, indoor exposure to heat is the underlying cause in a considerable fraction of heat-related morbidity and mortality. Notably, this can be observed in many US cities despite the high prevalence of mechanical air conditioning in the building stock. Therefore, part of the effort to reducing the overall vulnerability of urban populations to heat needs to be dedicated to understanding indoor exposure, its underlying behavioral and physical mechanisms, health outcomes, and possible mitigation strategies. This dissertation is an effort to advance the knowledge in these areas. The cities of Houston, TX, Phoenix, AZ, and Los Angeles, CA, are used as testbeds to assess exposure and vulnerability to indoor heat among people 65 and older. Measurements and validated whole-building simulations were used in conjunction with heat-vulnerability surveys and epidemiological modelling (of collaborators) to (1) understand how building characteristics and practices govern indoor exposure to heat among the elderly; (2) evaluate mechanical air conditioning as a reliable protective factor against indoor exposure to heat; and (3) identify potential impacts from the evolving building stock and a warming urban climate. The results show strong associations between indoor heat exposure and certain health outcomes and highlight the vulnerability of elderly

populations to heat despite the prevalence of air conditioning systems. Given the current construction practices and urban warming trends, this vulnerability will continue to grow. Therefore, policies promoting climate adaptive buildings features, as well as better access to reliable and affordable AC are needed. In addition, this research draws attention to the significant potential health consequences of large-scale power outages and proposes the implementation of passive survivability in regulations as one important preventative action.

DEDICATION

I dedicate this work to my lovely wife, Mahya, my kind parents, Nasser and Behnoush, and my little sister, Bahar.

This would have not been possible without their support, unconditional love, and countless sacrifices.

I love you all!

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1. INTRODUCTION

1.1. Background

1.1.1. Human thermoregulation and exposure to heat

The temperature-dependent processes that support biological life act as evolutionary forces that select for the ability to maintain constant core body temperature in animals (Muller 1995). In humans (endotherms), these evolutionary forces resulted in an ability to regulate core body temperature (at around 37 ˚C) through a balance of heat production and loss (Lim, Byrne, and Lee 2008). When the thermal environment disrupts this balance by increasing (or decreasing) the heat transfer to the body, several mechanisms are activated in response (e.g., water evaporation from the skin, shivering) (Ivanov 2006). If thermoregulation fails to maintain core body temperature at the optimal baseline, exposure to excess heat (and cold) can result in a variety of negative health impacts. Due to the significant dependence on age, sex, gender, existing health problems (e.g., diabetes) and other factors, it is not possible to associate health outcomes with specific core body temperatures. Nevertheless, documented impacts of moderate overheating (generally, less than 38 ˚C) include impairment in basic body functions such as respiration, circulation, immune response, kidney function, and cognitive performance. Between 38 and 39 ˚C, capacity for physical work diminishes, and cognitive performance is impaired in an average person. Heat stroke generally becomes a possibility at temperatures above 39 ˚C, while core body temperatures above 40 ˚C are considered life threatening (Ivanov 2006; Barreca 2012; Grogan and Hopkins 2002; Holmes, Phillips, and Wilson 2016; Ramsey 1995). At the highest range, core body temperatures above 42

˚C are reported to damage cellular cytoskeleton and impair functions of the central nervous system (Moseley 1993; Shapiro and Seidman 1990). Notably, long-term exposure to moderate overheating also has significant implications. For example, even mild heat exposures at night can disturb circadian cycles and reduce sleep quality and quantity (Muzet et al. 1983; Obradovich et al. 2017), which has several negative impacts on physical and mental wellbeing of humans. Similarly, cardiovascular strain due to prolonged exposure to heat, especially in the elderly, increases the risk of future implications (Kenney, Craighead, and Alexander 2014). Therefore, even though some evidence suggests a decline in vulnerability of human populations to extreme heat (Sheridan and Allen 2018) - likely due to a combination of growing access to air conditioning and health care - heat continues to be a key contributor to a large number of morbidity and mortality cases (Pachauri et al. 2014).

1.1.2. Heat-related mortality and morbidity and the role of indoor exposure

Reliable data on heat-related mortality and morbidity are uncommon - even in developed countries - due to challenges of generating and managing accurate public health records [1] (CDC 2017). In addition, cardiovascular and respiratory problems due to prolonged exposure to heat (especially in the elderly) that cause the majority of heat-related deaths are often misclassified (Kenney, Craighead, and Alexander 2014). While acknowledging these limitations, data from several national and regional databases can be cited. According to United States Center for Diseases Control (CDC), from 1999 to 2010,

[1] Data availability is one of the reasons for focusing on the United States in this dissertation. Additional justification for this selection is provided in Section 1-3.

heat killed 7,415 US citizens[2] (Prevention 2012). In addition, estimates suggest that the number of non-fatal cases of in-patient hospitalizations are at least an order of magnitude higher (CDC 2017). For example, an analysis by Choudhary et al. revealed that 28,000 morbidity cases occurred between 2001 and 2010 in 20 states that participated in a joint tracking program (Choudhary and Vaidyanathan 2014).

Notably, there is a significant disparity in vulnerability of different population groups to heat. A well-documented factor in vulnerability to heat is age. On average, elderly have a poorer physiological response and a decreased ability to sense heat. Moreover, potential decrease in cognitive performance can reduce the probability of taking adaptive measures in the elderly (Klenk, Becker, and Rapp 2010; Zanobetti et al. 2012; Kenny et al. 2018). As a result, a disproportionate number of fatalities occur within this age group (Laaidi et al. 2011; CDC 2013). Other important factors are socio-economic status, underlying climate, the surrounding micro-climate, and previous health implications (Putnam et al. 2018; D.M. Hondula et al. 2015; Fraser et al. 2016).

With respect to the location of exposure, indoor environments (and in specific, residences) are identified as the place of injury in a significant portion of mortality and morbidity cases (Holmes, Phillips, and Wilson 2016; Kenny et al. 2018; CDC 2013; MCDPH 2016). During typical summers, indoor exposure is the underlying cause in around 40% of heat fatalities (NWS 2016; MCDPH 2016). Under extreme events,

[2] For comparison, mortalities due to cold weather are roughly two times higher. However, as the second weather related killer, heat kills 5 times more people that floods, storms, and lightings combined. Also, it should be noted that statistics published by National Weather Service (NWS) are significantly different than those from CDC and identify heat as the number one weather-related killer in the US.

between 50 to 85% of fatalities typically occur in a place of residence (CDC 2013; Fouillet et al. 2006; Cadot, Rodwin, and Spira 2007). This is in part, due to the fact that human populations - especially in modern urban societies - spend a large portion of their day indoors (Brasche and Bischof 2005; Klepeis et al. 2001). In addition, elderly and the very young, that comprise the most vulnerable group, spend more time indoors than the general population (Almeida-Silva, Wolterbeek, and Almeida 2014). Accordingly, based on the trends in population ageing (Wiener and Tilly 2002), significance of indoor exposure to heat (especially in residences) can potentially increase over the next decades, even if the climate remains the same.

1.2. Characterizing the literature on indoor exposure to heat

Because of the importance of indoor exposure to heat, assessing its risk factors as well as possible mitigation strategies is an active area of research. In environmental health assessments, health risks are often expressed as functions of hazard, exposure, and vulnerability (Figure 1). In this context, hazard can be characterized as periods of hot weather, with two key contributors: (1) urban development in harsh climates (e.g., southwest United States), and (2) urban induced warming and climate change. The second component (exposure), is the indoor thermal conditions in response to the outdoor heat (hazard) that is mediated by the building. Finally, vulnerability refers to sensitivity of occupants to exposure that includes their physiological response to heat, as well as their adaptive capacity.

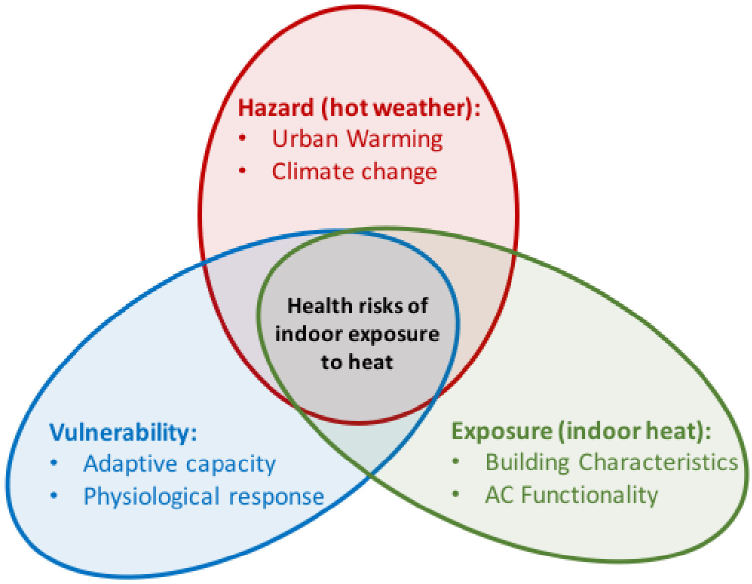

Figure 1. health risk components of indoor exposure to heat.

In this dissertation, the existence (and to some extent, potential intensification of) the hazard (heat in urban areas) is considered an axiom. This is supported by recorded weather data in many cities across the United States (Stone, Vargo, and Habeeb 2012) (the focus of this study) as well as the overwhelming majority of future projections that show a high probability of more intense and frequent heatwaves due to urban induced warming and climate change (Bartos and Chester 2014; Krayenhoff et al. 2018). Hence, the main focus of this dissertation is on the remaining components of risk: vulnerability (chapter 2) and exposure (chapter 3). Accordingly, the literature reviewed here has been divided based on these two perspectives:

1.2.1. Vulnerability

As shown in Figure 1, vulnerability to indoor exposure to heat has two components; physiological response and adaptive capacity.

The literature that is dedicated to physiological responses includes epidemiological studies in which researchers try to associate certain health outcomes (e.g., sleep loss, blood pressure, mortality) with heat exposure, and identify key contributing factors. The health outcomes data may come from health records of healthcare providers and local governments (Son et al. 2011; Knowlton et al. 2009; Pirard et al. 2005), or authors' own experiments and data collection (Y.-M. Kim et al. 2012; Basu and Samet 2002). Notably, few of the studies rely on exposure data gathered inside residential buildings because of challenges in generating such data at large scale. As an alternative, researchers often use data from nearby weather stations as a surrogate for indoor exposure. However, by disregarding the role that buildings play as mediators between indoor and outdoor environments, this approach fails to capture a key component of overall exposure (O'Lenick et al. 2019). For example, Basu and Samet (2002) monitored thermal environments of 42 senior citizens in Baltimore and found a positive correlation between skin temperature and temperature of the immediate surroundings (measured on clothing), but observed no correlation with temperatures recorded at nearby weather stations. It is noteworthy that this observation is potentially more conclusive in climates hotter that Baltimore, MD, with a higher AC prevalence. Therefore, despite the overwhelming evidence that implicates exposure to heat inside residences as a key factor from a statistical standpoint (see (MCDPH 2016; Fouillet et al. 2006)), there are limited data to provide explanation from an epidemiology point of view[3]. One of the few efforts in this line of research is the work done by Kim et al.

[3] It is noteworthy that there are ample studies and reports on relationships between indoor thermal conditions and thermal comfort, which is the subjective satisfaction with thermal environment and is a

(2012) on 20 elderly individuals in Seoul, South Korea. They observed a statistically significant decrease in diabolic (2.05 mmHg) and systolic (1.75 mmHg) blood pressures per 1 ˚C increase of the daily mean indoor air temperature, which was a significantly stronger correlation than that with outdoor environment. The literature also includes some studies that focus on the relationship between indoor temperature and sleep quality and duration. For example, Muzet et al. (1983) observed significant decreases in REM cycle length of five young adult males by increasing room temperature from 13 to 15 ˚C. Although, most of the studies on this front rely on subjective self-reports and/or are conducted in experimental setups (test chambers) instead of subjects' own residence.

The second component of vulnerability is adaptive capacity, that is occupants' ability to mitigate their exposure by modifying their behavior or environment (e.g., leave the building or bring a technician to repair the AC unit when it fails during the summer). The literature on adaptive capacity includes studies that focus on non-physiological[4] aspects of vulnerability to heat. The goal of these studies can be characterized as finding explanatory variables of vulnerability to heat from past experiences and using them to (1) identify most vulnerable groups; and (2) improve their resiliency to heat. Examples of such studies on urban populations in the United States include (Uejio et al. 2011; Fraser et al. 2016; D.M. Hondula et al. 2015; Putnam et al. 2018; Reid et al. 2009; Wilhelmi and

distinctly different phenomenon than health implicating heat. In addition, a significant number of epidemiological studies have been done to correlate indoor exposure and different health outcomes in settings and circumstances other than individuals in their place of residence. This includes studies on thermoregulation of exercise, as well as heat exposure in industrial environments, most of which are only applicable to young healthy adults.

[4] Although, age and race are included in some of the high-level heat vulnerability studies.

Hayden 2010; Sheridan and Dolney 2003; Johnson et al. 2012; O'Neill, Zanobetti, and Schwartz 2005; Madrigano et al. 2015). Since characteristics of the built environment, including variables such as access to AC, are often included in the frameworks that are used to assess vulnerability, these studies provide high level insights on the role of indoor exposure to heat, including some of the underlying mechanisms. For example, in a study by O'Neill et al. (2005), central AC prevalence in a neighborhood explained some of the differences in heat-related mortality by race, whereas window unit AC did not. In another paper, a post-event analysis by Fowler et al. (2013) revealed that out of the 32 heat-related deaths in Maryland, Ohio, Virginia, and West Virginia during a June 2012 heatwave, 22 occurred indoors, with lack of functioning AC (due to a large-scale power outage) reported in 20 of them. The paper by Alam et al. (2016) is another example that tries to associate the EnergyStar rating (mostly, governing the envelope properties) of residential buildings with probabilities of heat-related health outcomes (death, emergency room visit, ambulance call, after hour doctor visit).

1.2.2. Exposure

Studies with an exposure perspective are mostly part of the architecture/building science literature and try to quantify exposure to heat under different scenarios. Notably, most of these papers (typically published in engineering or architecture journals) do not account for vulnerability (either physiological or socio-economic) in their analysis. Nevertheless, for certain climates/regions, the existing literature in this category is extensive, and thus, there is a relatively conclusive understanding on how building characteristics (e.g. envelope properties, natural ventilation, thermal mass) and occupant behavior (e.g. window operation) impact indoor overheating. Through measurements, simulations, or a combination of both, these studies focus on summertime indoor overheating during episodic heat events, mostly in climates with historically moderate summers where AC prevalence is very low. Hence, most of them are done on European climates (and some of the heating-dominated climates in Australia) and focus on buildings without AC (Mavrogianni et al. 2012; Oikonomou et al. 2012; Pathan et al. 2017; Beizaee, Lomas, and Firth 2013; Sameni et al. 2015; Adekunle and Nikolopoulou 2016; Dodoo and Gustavsson 2016; Mlakar and Strancar 2011; K. J. Lomas and Ji 2009; Kevin J Lomas and Kane 2013; Porritt et al. 2012; McLeod, Hopfe, and Kwan 2013). On the other hand, fewer studies of this kind have been done in on US cities[5]. A possible explanation for this limited attention is the high prevalence of mechanical[6] AC, which is believed to decouple indoor thermal environment from outdoor signals; or at the minimum, protect occupants from adverse health impacts of heat. Because of the underlying climate, existing building stock characteristics, as well as socio-economic and cultural factors, AC prevalence across central and northern Europe is very low. For example, in the UK (the most studied country in the literature), less than 1% of houses and flats have mechanical cooling (Barford 2013); whereas in the United States, around 90% of homes have some type of AC (EIA 2015). As Figure 2 shows, the AC prevalence in new constructions is increasing in all regions of the United States and has already reached 100% in certain regions. Notably, the few studies that take a physics-based

[5] It should be noted that the focus here is on health-implicating heat. Hence, the extensive literature on indoor thermal comfort from a design perspective (including many done on US climates) are not being neglected.

[6] Throughout this text, “mechanical AC” or “mechanical cooling” refer to any cooling device that relies on mechanically induced pressure cycles of a refrigerant (e.g. central AC and window/room units). This does not include ceiling fans.

approach to assess indoor overheating in residential buildings in North American climates focus on scenarios where mechanical AC is temporary unavailable (e.g., due to a power outage) (Nahlik et al. 2016; D. J. Sailor 2014; Bennet 2016; Samuelson et al. 2016; USGBC 2014).

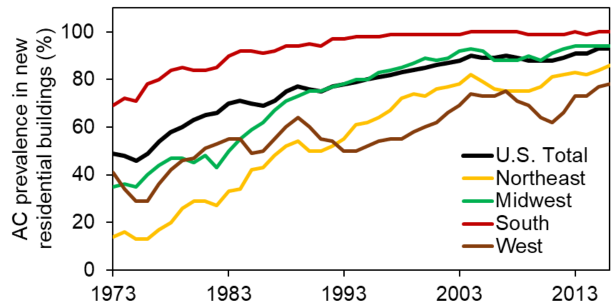

Figure 2. Growing rate of AC penetration into U.S. residential building stock. Data from U.S. Census Bureau.

The affordability and availability of AC also paves the way for cheaper design and construction practices that are not climate-adaptive. Thus, making buildings more prone to indoor overheating in its absence. Quintessential examples include the wide-spread use of lightweight wood-frame construction with low thermal mass, as well as neglecting natural ventilation and solar heat gain control in the building design in hot arid cities such as Phoenix, AZ. According to (EIA 2015), 55% of residential buildings in mixed-dry/hot-dry climates of the United States are single-family detached units with no shared walls, while less than 12% have walls with thermal mass (concrete block or brick). In addition, almost half of them have single pane windows with a high heat gain coefficient. Nevertheless, more than 65% of these residential units are kept at temperatures below 26 °C (80 °F) throughout the summer by means of mechanical AC.

1.3. Identified research gaps and their significance

There are considerable gaps in the literature on indoor exposure to heat, its impacts, and solutions from both vulnerability and exposure perspectives.

In the building science (the exposure) literature, the main knowledge gap is our understanding of indoor exposure to heat, its underlying physical mechanisms, impacts of building characteristics, and possible mitigation strategies in climates and locations with high AC prevalence – mostly, in the US. This includes different modes of AC non-functionality such as power outages or broken AC units (see Section 3-1-2 for classification). This is a significant limitation considering the overwhelming evidence that suggests indoor overheating can occur in the physical presence of AC. For example, in Maricopa County, AZ, in all cases of heat-related deaths associated with an indoor place of injury in the summer of 2016 (61 out of the total 154 heat-related deaths that year), an AC system was reported to be present, but in some state of disrepair (MCDPH 2016). Common causes of non or semi-operational AC include high electricity cost (which results in higher thermostat set points or a complete shutdown), not being able to afford fixing a broken unit, a temporary power outage, or an undersized AC system that cannot meet the cooling demand during extreme heat events (e.g., small window unit systems). In addition, there is empirical evidence suggesting that even with a fully functional AC unit and enough financial resources, some vulnerable groups (especially, the elderly) might not be able to properly use it because of the limited ability to sense heat (Dufour and Candas 2007). For example, a measurement campaign in 30 buildings with residents aged 65 and older in Detroit, MI, recorded indoor air temperatures as high as 34 ˚C in buildings that had functional AC (White-Newsome et al. 2012). Heat-vulnerability surveys provide additional strong evidence of indoor heat exposure despite the physical presence of an AC system. For example, Hayden et al. (2017) conducted a survey of 901 households in Houston, TX, and reported that although 87% of respondents had central air conditioning, 37% of them “felt too hot in their home” during the summer. In addition, a fifth of participants reported experiencing some heat-related symptom, while 75% reported experiencing it more than once. Notably, 95% of respondents who experienced these symptoms inside their homes had some type of AC (central or window units) and 14% of respondents stated that the cost of electricity prevented them from using their AC. In another study, Hayden et al. (2011) conducted a door-to-door survey of 362 households in Phoenix, AZ and reported similar findings. While 89% of participants had air conditioning inside their homes, 38% of them “felt too hot” during the summer of 2009. Authors of this study reported that 89% of respondents who experienced heat-related symptoms had AC. An important explanatory factor for why presence of AC alone was insufficient to avert heat-related symptoms was the cost of running and maintaining an AC system (36% of respondents had problems paying their electricity bill, and 6% were not able to afford fixing a broken unit) (White-Newsome et al. 2012). The other mode of AC inaccessibility that can potentially affect a higher number of people is large-scale power outages during heat events (Nahlik et al. 2016; Baniassadi, Heusinger, and Sailor 2018; Baniassadi and Sailor 2018; Bennet 2016; Samuelson et al. 2016; D. J. Sailor 2014; David 2019). For example, in the summer of 2012, a series of thunderstorms followed by a heatwave in the U.S. Midwest resulted in a power outage that caused at least 20 heat-related deaths in a short period due to lack of access to AC (Fowler et al. 2013). While there is no data available on the number of non-fatal cases of heat-related implications during that period, estimates based on previous events (CDC 2013) suggest that they are an order of magnitude higher than the mortality cases. Despite ongoing improvements in the resilience of power infrastructure, the risk of major power outages will persist and potentially grow (Y. Yang, Nishikawa, and Motter 2017). Between 2000 and 2015, in the United States alone, 525 incidents of power outages lasting longer than 10 hours and with more than 100,000 affected customers were reported (Figure 3). While more than 90% of the failures were caused by weather-related disturbances (including system overload during heat waves (Auffhammer, Baylis, and Hausman 2017)), human causes such as vandalism, equipment failure, and load shedding are also reported. In addition, national security authorities are increasingly concerned by the prospect for cyber terrorism or state-sponsored attacks on power generation and transmission infrastructure (Xiang, Wang, and Liu 2017). In contrast to AC equipment failure in a single home, a major power outage would diminish individuals’ ability to take refugee from heat in other buildings within the community (Fraser et al. 2016). Moreover, because of the large scale of utility system outages, the capacity of medical facilities to respond to the situation may be substantially challenged (Bernard and McGeehin 2004), compounding the health impacts during more extreme cases (David J Sailor et al. 2019).

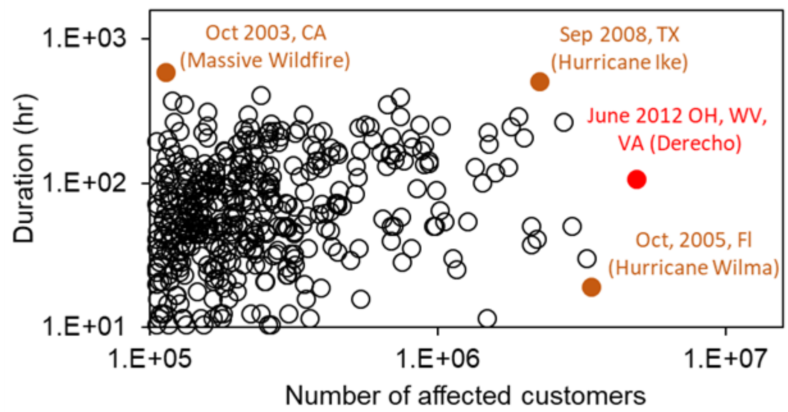

Figure 3. Magnitude and duration of power outages in the U.S. from 2000-2015. Incidents lasting less than 10 hours or affecting less than 100,000 customers are excluded. Figure from author's published work (David J Sailor et al. 2019).

From the vulnerability perspective (its physiological component), the main knowledge gap is the lack of data to demonstrate empirical relationships between indoor exposure and health outcomes. Especially, for people inside their residences (Holmes, Phillips, and Wilson 2016; Kenny et al. 2018; Anderson et al. 2013). Regarding the adaptive capacity component, occurrence of overheating in the presence of mechanical AC (as discussed above) casts doubt on a common assumption in socio-economic vulnerability assessments that considers AC as a binary variable [7]. Therefore, the limited knowledge on the role of buildings as a protective factor in climates with high AC prevalence (Section 1-2-2) results in lack of physical evidence for socio-economic assessments of vulnerability to heat.

Collectively, these knowledge gaps limit our ability to 1) assess health-risks associated with indoor exposure to heat in certain climates; and 2) identify solutions that

[7] Variables such as income can potentially provide some insight by acting as correlates of AC-functionality. Although there is no empirical evidence to support this; especially for the elderly.

directly affect the end-points (health-risks). This dissertation is an effort to address these issues.

1.4. Research objectives and the dissertation structure

1.4.1. Objectives and scope

The research objectives of this dissertation were defined based on the identified knowledge gaps and their importance:

Objective 1: Estimate citywide indoor heat exposure in Houston, TX (for integration into a health-outcomes model)

This includes the author's contributions to a collaborative effort aimed at implementing indoor exposure to heat in an epidemiological health-outcomes model to test the hypothesis that including time-series of estimated indoor exposure improves epidemiological models. The other goal was to identify associations between indoor heat and certain health outcomes in the elderly.

Objective 2: Quantify exposure to indoor heat in climates with high AC prevalence

This includes physics based (simulation and measurements) approaches to understanding indoor thermal conditions inside residential buildings in climates that have a high AC prevalence, as well as impacts from buildings characteristics, underlying climate, and occupant behavior.

Objective 3: Identify potential compounding factors and mitigation strategies

Compounding factors include potential impacts of climate change and urban induced heat, as well as any trend in construction practices that can intensify indoor overheating. Mitigation strategies are defined as cost-effective solutions that are in synergy with other important targets – mainly, energy efficiency of buildings.

Based on the identified limitations in the literature, this study is done on hot climates of the United States with relatively high AC prevalence. For the first objective, the scope is limited to Houston, TX, while Phoenix, AZ, Los Angeles, CA, are also studied for the second and third objectives[8] (See Section 3-1-1 for justification of this selection). In addition, the focus is on elderly population (65 and older) because of their higher physiological sensitivity and well-documented reduced adaptive capacity to heat.

1.4.2. Dissertation Structure

This dissertation has two core chapters (2 and 3). Chapter 2 focuses on the first objective, using Houston as a testbed. The Author's efforts in this chapter are within a broader context of a collaborative research project (see Section 2-2-1-3 for details). Chapter 3 focuses on the last two objectives and expands the analysis to two other cities (Phoenix and Los Angeles). The final chapter (4) is dedicated to a synthesis of the findings that relates results to the mentioned knowledge gaps in the literature. In addition, it includes limitations, as well as recommendations for future research.

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[8] Although, some of the resulting publications from this work include other locations/climates (see the publication list in each chapter for details)

2. VULNERABILITY TO INDOOR HEAT; CASE STUDY OF HOUSTON, TEXAS

This chapter has two Sections: (1) a summer measurement campaign in a small sample of buildings in Houston, and (2) implementation of simulated indoor thermal conditions in an epidemiological model to identify the health outcomes of indoor exposure to heat among the elderly (65 and older) population in Houston. Due to the interdisciplinary nature and broad scope of this chapter, the author's contribution was necessarily part of a broader collaborative effort that included scientists with backgrounds in environmental epidemiology, public health, urban climatology, and geographical information systems. Throughout the chapter, contributions from other researchers are acknowledged as appropriate in footnotes.

2.1. Measurement Campaign

The goal of the measurement campaign was to generate an empirical dataset of indoor exposure to heat and its underlying factors in a small sample of residences in Houston, TX. In addition, data and observations from the campaign (especially adaptive behavior) informed several aspects of the modelling effort in the second Section of the chapter, as well as the entire modelling effort in Chapter 3.

2.1.1. Methods

Summertime indoor temperature, relative humidity, and CO_2 were monitored over two consecutive summers (2016 and 2017) in 23 buildings in Houston that had residents 65 and older[9]. At a minimum, data was recorded from each building spanned two months.

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[9] The CO_2 data are not presented here because they are not within the scope of this dissertation.

The sample included private residences as well as small managed living facilities residing around 10 people. From the small pool of participants that agreed to be recruited by Houston Department of Public Health, buildings were selected to maximize geographic variation (Figure 4). In addition, post measurement interviews were conducted to better understand underlying behaviors and building characteristics contributing to overheating in buildings.

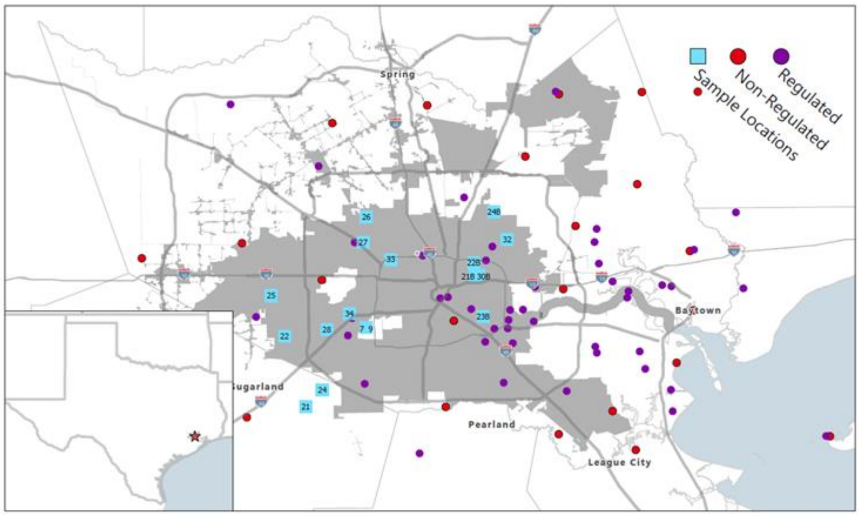

Figure 4. Geographic distribution of samples in Houston, TX. Figure credit: Paige Hoel, NCAR

2.1.1.1. Measurements

In each building, a set of two to four HOBO MX1102 loggers (Dry-bulb temperature accuracy: ±0.21°C from 0° to 50°C, Relative Humidity accuracy: ±2% from 20% to 80% typical to a maximum of ±4.5%; below 20% and above 80% ±6% typical)

See *(Baniassadi, A.; Sailor, D.; O'Lenick, C. Indoor air quality and thermal comfort for elderly residents in Houston TX—a case study. In Proceedings of 7th International Building Physics Conference; pp. 787 – 792)* for the analysis regarding CO_2.

were installed at various locations to record environmental parameters (Figure 5)[10]. The measured variables were recorded in at least two rooms (namely, a bedroom and the living room) in each building at 30-minute timestamps. As demonstrated in Figure 5, to the extent possible, sensors were not placed in proximity of heat or humidity sources (e.g., electric appliances). Occupancy status was recorded via HOBO UX90-005 Occupancy/Light Data Loggers (detection performance: 94° (±47°) horizontal; 82° (±41°) vertical) and was used to filter out the unoccupied hours during which no exposure took place.

Figure 5. Sensor installation (occupancy, T, RH, and CO_2 loggers) in sample buildings.

2.1.1.2. Overheating metric and thresholds[11]

Thermal discomfort (lack of satisfaction with the thermal environment) and health-implicating heat are distinct phenomena and thus, thresholds and guidelines that

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[10] The author acknowledges support from Mr. Peter Chen and Mr. Youjun Qin from Houston Health Department (HHD) who helped with sensor installation, made regular visits to facilities, and extracted all sensors. In addition, Julie Pham (Arizona State University) helped partly with sensor programming in the summer of 2017. Sensor installation in the summer of 2016 (7 buildings) was done entirely by Dr. David Sailor (Arizona State University)

[11] Unless otherwise stated, all overheating metrics and thresholds in this document refer to the ones discussed here.

are available for the former (such as ASHRAE standard 55 or CIBSE guidelines for overheating definition) cannot be used to assess the latter. Health-implicating heat is a result of unsustainable core body temperature, and far exceeds any thermal comfort threshold. As seen in Figure 6 (Bianca 1968), the zone of Homeothermy (C-C') within which the core body temperature of the individuals remains constant is broader than the zone of thermal comfort (A-A') within which individuals feel comfortable.

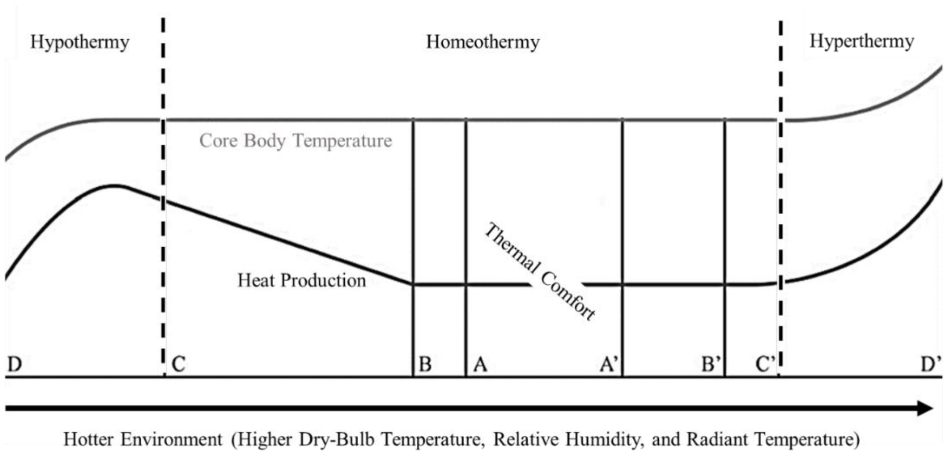

Figure 6. Thermoregulation of body in response to external conditions – after Bianca (1968).

Since the literature on reliable metrics and thresholds for health-implicating heat in residential buildings is very limited, some researchers use data that were originally developed for non-residential environments. The limitation of this approach is that these thresholds are developed for young healthy individuals and cannot be used for more vulnerable groups such as elderly and children. For example, Holmes et al. (2016) used National Institute for Occupational Safety and Health (NIOSH) guidelines for workers in industrial environments to derive thresholds applicable to residential buildings. Similarly, studies that cite the Discomfort Index from (Epstein and Moran 2006), such as (Ramakrishnan et al. 2016; Ren, Wang, and Chen 2014; Alam et al. 2016; Baniassadi and

Sailor 2018; Baniassadi, Heusinger, and Sailor 2018), are in fact relying on thresholds established for army personnel. Based on their literature review, Kenny et al. (2018) state that "*to date there remains a paucity of research directed at defining 'high risk' ambient conditions for the most vulnerable".* Similarly, after reviewing 96 peer-reviewed articles, Anderson et al. (2013) concluded that "*the data are sparse and inconclusive in terms of identifying evidence-based definitions for thresholds".*

In this study, based on the suggestion by Holmes et al. (2016), Wet-Bulb Globe Temperature WBGT was used as the heat metric. This metric includes the impacts from dry-bulb temperature, relative humidity, air velocity, and radiative exchange. In addition, it is recognized and used globally to study indoor overheating (although, mostly in non-residential settings). Regarding the overheating threshold, after a broad review of the literature, a WBGT of 23 ˚C was selected for the population group of 65 and older, while acknowledging the wide range of suggested thresholds: between 21 ˚C (based on World Health Organization guidelines at typical residential relative humidity values) to 28 ˚C (based on the work of Holmes et al. (2016)). It should be noted that temperatures above which occupants show signs of unsustainable core body temperature are highly dependent on several intrinsic factors such as sex, age, acclimation, hydration, and existence of chronic disease (in particular, cardiovascular problems or type 2 diabetes) (Kenny et al. 2018). Nevertheless, having a threshold is helpful as it enables better interpretation of the results.

2.1.1.3. Post-measurement interviews

Once the campaign was complete, data from all sensors were extracted and curated for further analysis. After filtering out unoccupied portions based on data from occupancy sensors as well as outliers that were due to sensor malfunction (Hurricane Harvey damaged a few of the sensor), Dry-bulb temperature and relative humidity data were used to calculate WBGT based on formulation described in detail in (Holmes, Phillips, and Wilson 2016). The two assumptions in this calculation included low indoor air velocity and identical dry-bulb and mean radiant temperatures. While the former is a common assumption in residential settings, the latter was validated by the author in (Baniassadi and Sailor 2018).

After the initial analysis of the data, buildings that overheated frequently were identified. Accordingly, several hypotheses were developed to explain the underlying causes of the outliers, which informed the post-measurement IRB approved interviews and site visits done by collaborators[12] in February 2018. The (related parts of) results from the interviews were reported back to the author through personal communications.

2.1.2. Results and discussion

2.1.2.1. overheating under normal conditions

Figure 7 shows the portion of occupied time during which indoor WBGT exceeded the 23 ˚C threshold. In third of the buildings in the sample, indoor thermal conditions exceed the threshold for more than 5% of the occupied time, which is the overheating time limit set by Chartered Institute of Building Service Engineers (CIBSE). Although this sample is significantly smaller than the survey sample (see Section 3-1-3), the percentage of homes that exceed both thresholds (a WBGT higher 23 ˚C for more

[12] Drs. Olga Wilhelmi, Cassandra O'lenick, and Mary Hayden from (National Center for Atmospheric research (NCAR), Boulder, CA)

than 5% of the time) is similar to the number of respondents in the survey (304 samples) who either experience heat-related symptoms or report feeling too hot inside their homes. This can be a potential justification for assuming that the small sample showed here is potentially a representative of the general elderly population in Houston.

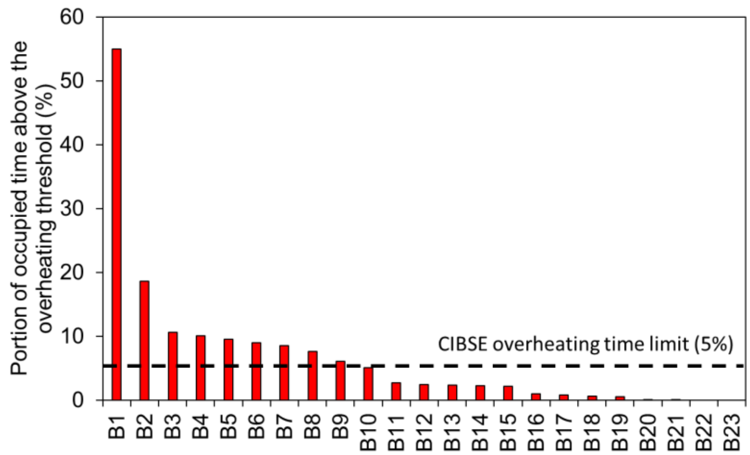

Figure 7. Summertime overheat status in sample buildings in Houston, TX.

The post-campaign interviews provided additional insight on the underlying causes of overheating (or its absence) in these buildings. In particular, they implicated occupant behavior and socio-economic component of vulnerability (mostly determined by AC functionality) as the main explanatory variables behind data in Figure 7. The following quotes are associated with three different buildings that the author characterized[13] as similar with respect to building properties:

[13] The author developed a standard frame-work for characterizing buildings during sensor installation and trained Peter Chen and Youjun Qin of HHD to conduct it. It included noting exterior wall type, shade on exterior walls, window type, level of insulation in attic, and taking pictures from cardinal angles. Author supplemented this with imagery from Google Earth. More detailed observations (for example, noting the window operation or number of occupants) were done per author's request during post-measurement interviews.

B1: *"The participant relied on window units to cool the home. The window units did not work well (or at all). Participant* ***could not afford*** *to fix the window AC units. Participant said they struggled to maintain comfortable temperature in their home all summer. On especially hot days, participant could not sleep until it cooled off enough at night (~10pm)."*

B6: *"The temperature setting was 81 degrees. Residents are likely low income/no income, have intellectual disabilities and mental health issues. We did not interview residents at site 22. We did interview a staff member. Based on our observations, the owner of this facility neglects his residents and the home."*

B20: *"Participant has well-functioning AC. Participant sets day time AC between 21-24℃ and lowers temperature setting to ~20 C at night. These are the temperature setting preferences of the participant. Participant did not lose electricity during Hurricane Harvey and had no issues with AC or power this summer."*

In these examples, AC functionality is the main determinant of indoor thermal conditions, with economic concerns, and limited physical and mental ability to adapt to heat as the underlying cause of its absence in B1 and B6, respectively. Notably, the set did not include any sample in which indoor thermal conditions could not be explained by observations regarding AC functionality.

2.1.2.2. Case study of Hurricane Harvey

Harvey, a category 4 hurricane that made landfall in Texas on Aug 25, 2017 resulted in a large-scale power outage that affected more than 336,000 customers. Therefore, some of the gathered data included indoor thermal conditions inside buildings that lost power. The data serves as a case study of a moderate heat disaster (the sky was overcast, and the temperatures remain relatively cool during the episode and most buildings regained power before the weather got back to normal)[14].

Figure 8 shows the indoor dry-bulb temperature in the three buildings that lost power on the midnight of Aug 27, 2017. Since the relative humidity remined close to 100% during the entire episode, WBGT was almost identical to dry-bulb temperature.

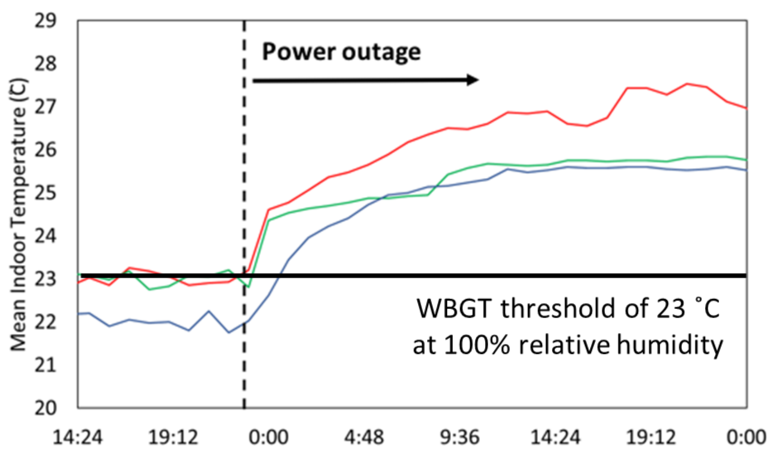

Figure 8. Indoor temperature in three sample buildings during power outages caused by hurricane Harvey

Due to relatively overcast skies in the immediate aftermath of the hurricane, ambient air temperatures fluctuated between 23 and 26 ˚C and indoor air temperatures remained below 27 ˚C during the power outage period. Nevertheless, since the indoor relative humidity reached 100%, indoor thermal conditions exceeded safe thresholds for much of the power outage period. It is important to note that, while the monitored

[14] In addition, the gathered data provided an opportunity to inform/validate efforts on modelling uncontrolled indoor thermal conditions (see Section 2-2-1-1). This includes the recorded physical variables (temperature and relative humidity) that were directly used to validate/tune EnergyPlus simulations as well as behavioral aspects obtained through post-measurement interviews that informed some of the assumptions in the model, including window operation and occupancy level.

buildings all regained electricity prior to the skies clearing and the ambient temperatures returning to typical late summer levels, up to 4,000 homes in Texas remained without power for several weeks. In such homes, the unsafe conditions were likely exacerbated by increases in both indoor humidity and air temperature. Thus, highlighting the importance of understanding heat exposure during large-scale power outages (explored in next chapter).

In all three buildings, occupants did not leave their homes during the episode. In one building (the red line in Figure 8), *"during and after Hurricane Harvey there were 5 extra people in the participant's home. Power was out the entire time the participant's family was staying in the home. They kept windows, doors, and the garage door open all day and all night until the power came back on. Participant said it felt very hot and humid in the home while the power was out"*[15]. In another building (the blue line in figure 8), *"the occupant opened windows and borrowed neighbor's generator to use a fan in the house"*[15]. While acknowledging the small sample size, these observations highlight that during extreme events, the number of interventions from occupants to mitigate indoor heat is very limited, and those who don't have the option of leaving their home (due to economic reasons, lack of supporting social network, or lack of physical ability) will remain exposed to indoor conditions throughout the episode. As will be discussed in the next chapter, building characteristics are the key determinants of the exposure intensity and duration under these scenarios.

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[15] Quote from interview notes.

2.2. Integration of indoor exposure into an epidemiology model

This Section of the dissertation is based on author's contribution to an epidemiological study[16] with the goal of evaluating the role of indoor heat exposure on heat-related mortality and morbidity among the elderly ($\geq$ 65 years) in Houston (domain shown in figure 9). Here, the focus is on "indoor heat" within the broader context of the epidemiology study. For details regarding the epidemiology analysis, as well as impacts from Ozone and outdoor thermal conditions, see (R. O'Lenick et al. 2019).

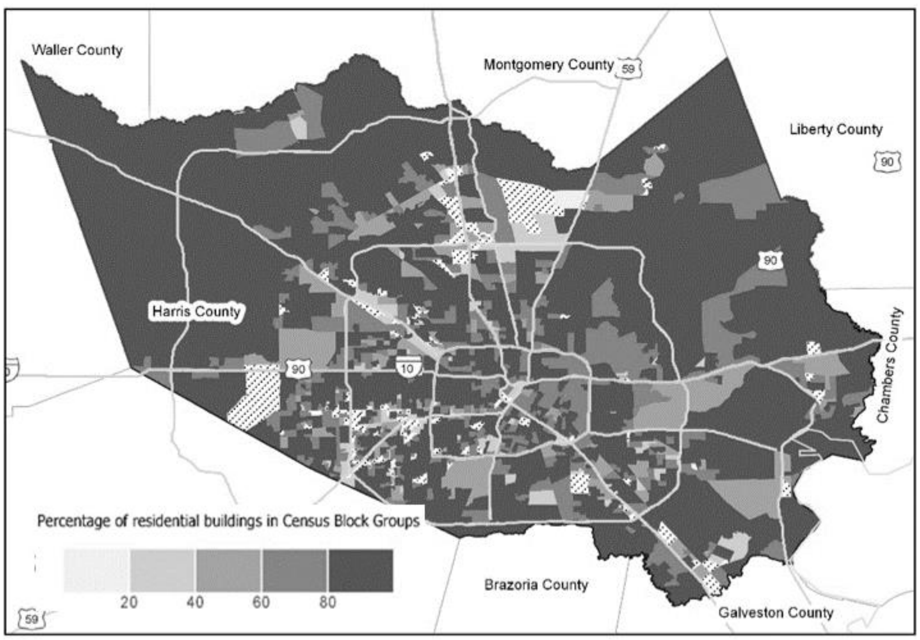


Figure 9. Study domain. Modified figure from (R. O'Lenick et al. 2019)

[16] Led by Dr. Cassandra O'lenick (NCAR)

2.2.1. Methods

2.2.1.1. Whole-building energy simulations

Whole-building energy models use physics-based equations to assess the thermal behavior of a building in response to the outdoor environment and internal loads. These models dynamically solve mass and energy balance equations for different air masses (zones) inside a building while considering all forms of heat and material transfer. Extensive research in this area has resulted in several robust tools available to engineers and designers. EnergyPlus, developed by U.S. Department of Energy (DOE) is commonly used in the literature (Baniassadi, Heusinger, and Sailor 2018; Ramakrishnan et al. 2017) and was used to simulate thermal conditions inside buildings for this analysis. Relevant modules of EnergyPlus have been validated in (Tabares-Velasco, Christensen, and Bianchi 2012; Mateus, Pinto, and Graça 2014; Gu 2007; Shrestha and Maxwell 2011; Yu et al. 2014; Loutzenhiser et al. 2009; Witte et al. 2011). In addition, EnergyPlus has passed the ANSI/ASHRAE standard 140 test (Crawley et al. 2004; Henninger and Witte 2010). With respect to the prediction of indoor thermal conditions, Zhuang et al. (2010) reported a maximum error of 8.3%. in temperature estimates. Alam et al. (2016) reported that the model was able to predict temperature with an average error of 0.7 ˚C. In addition, in (Sailor et al. 2019) the author has validated EnergyPlus's output (see Figure 10) based on data gathered in four residential buildings in Houston (two single-family homes during Hurricane Harvey) and Phoenix (two apartment units under artificial power outages in the summer of 2018). The details of this validation can be found in (Sailor et al. 2019).

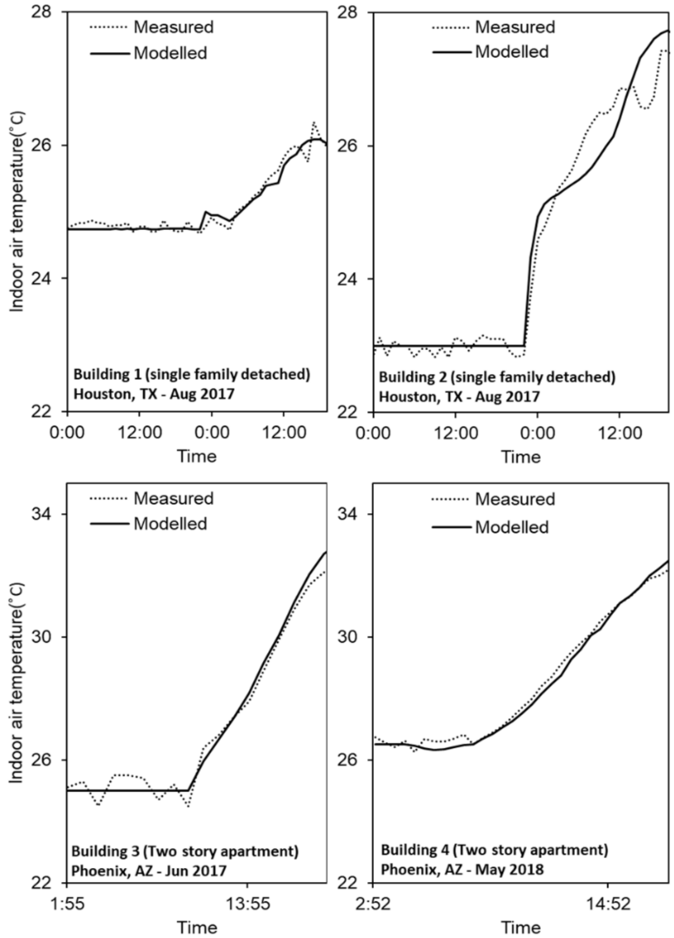


Figure 10. Indoor temperature from EnergyPlus simulations vs. actual measurement. Data in Phoenix is a better match because of the controlled and constant conditions. On the other hand, the samples in Houston include the uncertainties from occupant behavior. Nevertheless, this comparison shows that EnergyPlus can predict indoor temperatures with high accuracy. That includes instances of sudden loss of power.

The author used archetype building models representing the building stock of the domain because simulating individual buildings was neither feasible (because of the large domain) nor reliable (due to lack of information at the building level). Harris County tax assessor database[17] was used to generate 144 archetypes, representing the entire

[17] The tax assessor data included size, number of floors, exterior wall type, and qualitative description of the construction quality.

residential building stock of the domain. These archetypes were generated based on four types of exterior wall construction, three heights (number of floors) three sizes (<1,500, 1,500 - 2,500, and >2,500 sq.ft^2) and three types of descriptive quality. As a result, 97% of residential buildings within the domain are represented. Moreover, the author associated the envelope properties to descriptive qualities of buildings and their age based on different versions of International Energy Conservation Code (IECC), as well as (Yamamoto et al. 2010) (see Table 1).

Table 1. Envelope properties of archetypes.

	Descriptive Quality (from tax assessor data)		
Envelope properties	High	Medium	Low
Exterior wall insulation R-value (K. m²/W)	2	1.5	1
Ceiling Insulation R-value (K. m²/W)	6	4	3
Nominal air exchange rate (ACH)	0.4	0.9	1.4
Window U-value (W/K. m²)	3	5	5
Window Solar heat gain coefficient	0.25	0.4	0.4

For variables not found in the tax assessor data, national databases such as Residential Energy Consumption Survey (EIA 2015) from U.S. DOE were used. In addition, occupancy and plug-load schedules were input based on recommendations of Building America House Simulation Protocols (Hendron and Engebrecht 2010). In buildings without AC, it was assumed that windows are open when the ambient temperature is 2 °C below indoors. In the model, this was reflected by adding a natural ventilation object (0.3 ACH) based on (Howard-Reed, Wallace, and Ott 2002; Wallace, Emmerich, and Howard-Reed 2002). In buildings with AC, the author assumed a constant[18] thermostat setpoint of 23 ˚C (dry-bulb) based on the data from (EIA 2015).

2.2.1.2. Weather data

Hourly meteorological conditions in Houston for 2000-2015 have been previously simulated[19] using the High-Resolution Land Data Assimilation System (HRLDAS). Details of HRLDAS simulations can be found in (Monaghan et al. 2014). Because HRLDAS data had a fine scale resolution, the region was delineated to provide some spatial variance in building simulations. The author created five zones to represent the variation in weather across Harris County based on proximity to the coast and the center of the City of Houston (see Figure 11). The HRLDAS output was spatially averaged[20] within each zone to generate weather data files for building simulations.

[18] This is an important limitation that is discussed in detail in the next chapters. However, currently, there is no reliable data to account for this.
[19] Data was obtained from simulations conducted by Dr. Andrew Monaghan and his colleagues at NCAR.
[20] Post-processing was done by Dr. Jannik Heusinger and Mr. Peter Crank at Arizona State University.

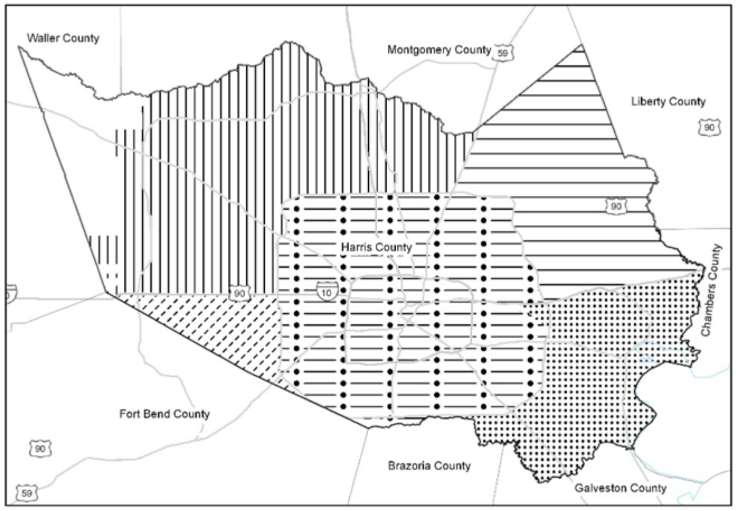


Figure 11. Spatial representation of the five zones used in indoor heat exposure simulations. Modified figure from author's coauthored paper (R. O'Lenick et al. 2019).

2.2.1.3. Integration into the health-outcomes model

The EnergyPlus simulations resulted in time-series of indoor temperature and relative humidity in all archetypes for the entire analysis period. As the next step, the author used GEOID's in the tax assessor database and calculated the fraction of buildings corresponding to each archetype in every census block group[21]. Then, these fractions were used to weight the estimated indoor variables. Figure 12 shows the indoor exposure estimation process. The resulting estimates were then directly applied into the health outcomes model. All the information, steps, and codes required to replicate the indoor temperature estimates are provided in appendix 1.

[21] Author acknowledges contributions from Jennifer Boenhart, a GIS specialist at NCAR, who helped analyzing the Tax Assessor's data.

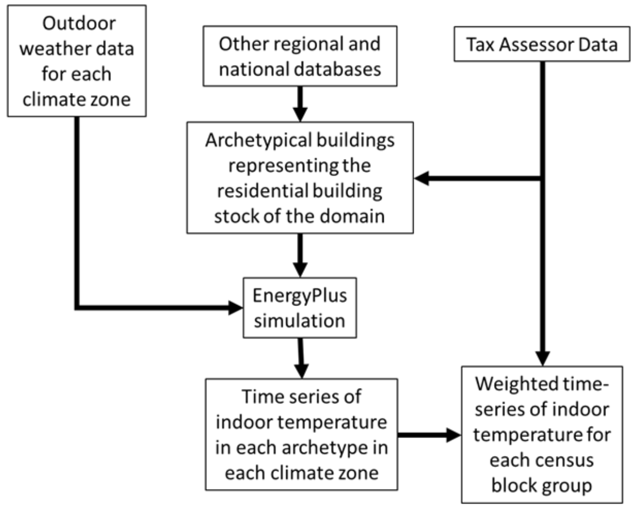


Figure 12. The workflow process of indoor temperature estimation process

2.2.2. Results and discussion

2.2.2.1. Estimates of indoor exposure

Figure 13 is a demonstration of the type of data that was fed into the health-outcomes model.

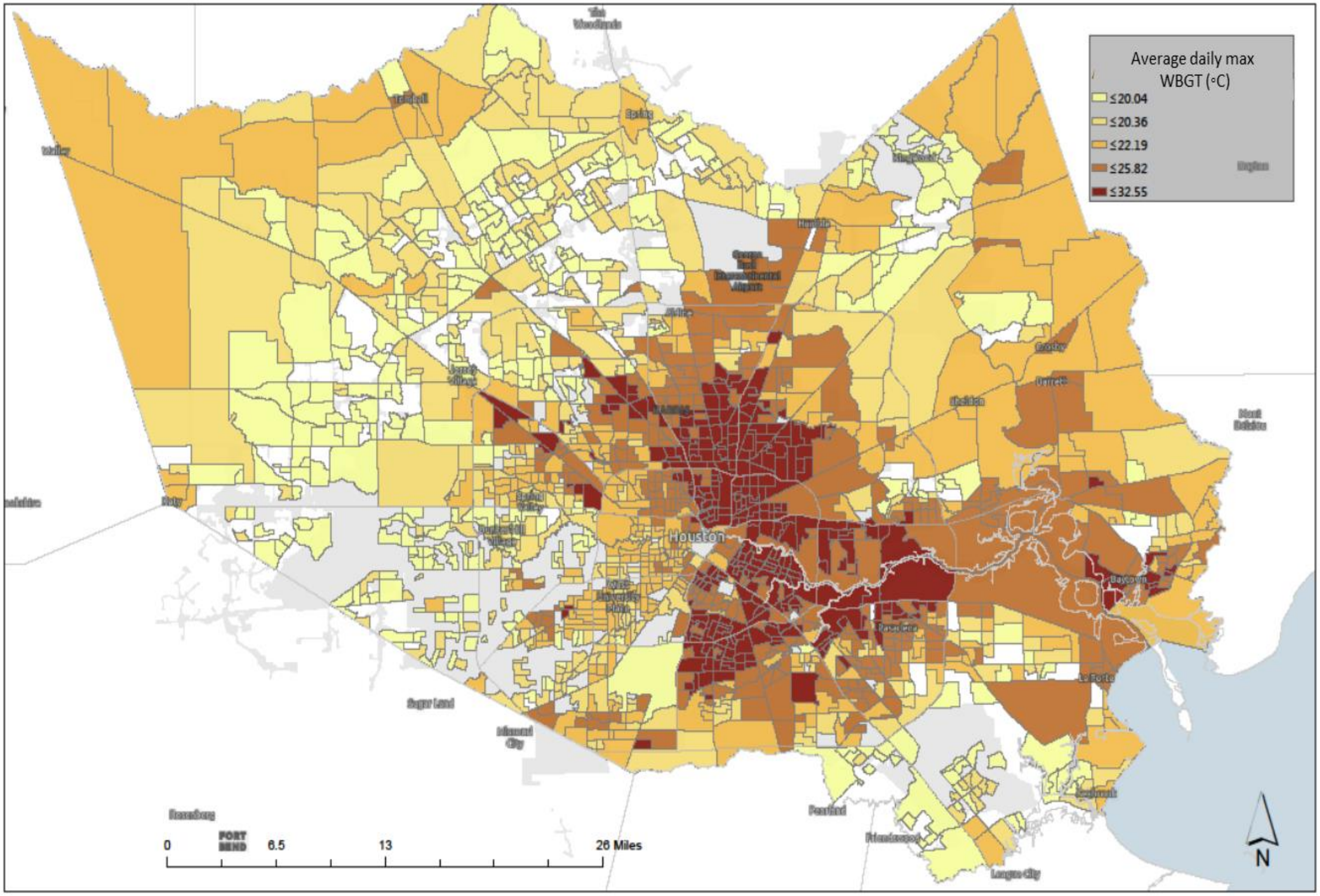


Figure 13. Estimated average daily max WBGT at census block group (summer of 2010). Paige Hoel (NCAR) helped generate this grap

While this figure does not demonstrate temporal variability, it shows that the correlations between indoor and outdoor temperature time-series are weak, which can be explained by high AC prevalence in Houston. Considering the significant geographic variability of indoor exposure to heat, a moderate correlation was found between indoor heat exposure estimates and common indicators of socio-economic status such as income, and racial composition of each census block group (compare the inner-city neighborhoods with the suburbs). However, the key explanatory variable for this variation was found to be the AC prevalence in each census block group. Nevertheless, as mentioned in the next section, using AC prevalence (as a static number) by itself does not improve the robustness of the health-outcome framework as near as the estimated time-series of exposure.

2.2.2.2. Health impacts of indoor exposure to heat

This section is a summary of results from the health-outcomes analysis as it pertains to the indoor exposure component. Additional details regarding role of outdoor component, and Ozone exposure can be found in (R. O'Lenick et al. 2019). Table 2 shows the summary of findings from incorporating the estimates for indoor exposure at census block group level into an epidemiological model of the entire city (R. O'Lenick et al. 2019).

Table 2. Odds Ratios (OR) between indoor heat exposure and health outcomes (Table from (R. O'Lenick et al. 2019))

	Heat-related Diagnoses		Circulatory Diagnoses	
	Mortality	Mortality & HA	Mortality	Mortality & HA
	OR (95% CIs) per 5 °C	OR (95% CIs) per 5 °C	OR (95% CIs) per 5 °C	OR (95% CIs) per 5 °C
Indoor Max WBGT(°C)				
Lag 0	**1.18 (1.05, 1.34)**	1.08 (0.99, 1.17)	**1.27 (1.10,1.46)**	1.08 (0.98,1.19)
Lag 1	**1.15 (1.02, 1.30)**	**1.16 (1.07, 1.26)**	**1.22 (1.06,1.41)**	**1.16 (1.05,1.29)**
Lag 2	1.01 (0.89,1.14)	1.04 (0.95, 1.12)	1.06 (0.92,1.21)	1.04 (0.94,1.15)
Lag 0-2	**1.20 (1.02, 1.40)**	**1.15 (1.04, 1.28)**	**1.31 (1.10,1.57)**	**1.16 (1.02,1.32)**
Indoor Max Temp (°C)				
Lag 0	**1.11 (1.02, 1.20)**	1.05 (0.99, 1.10)	**1.14 (1.04, 1.25)**	1.05 (0.98,1.12)
Lag 1	**1.08 (1.00, 1.17)**	**1.10 (1.04, 1.16)**	**1.12 (1.02, 1.23)**	**1.11 (1.04,1.18)**
Lag 2	0.98 (0.91, 1.06)	1.02 (0.97, 1.08)	1.01 (0.92, 1.11)	1.03 (0.97,1.10)
Lag 0-2	1.10 (0.99, 1.22)	**1.09 (1.02, 1.17)**	**1.16 (1.03, 1.30)**	**1.11 (1.02,1.20)**
Indoor Min Temp (°C)				
Lag 0	1.11 (0.90, 1.36)	1.05 (0.92, 1.19)	**1.26 (1.00, 1.58)**	0.99 (0.84,1.16)
Lag 1	**1.23 (1.01, 1.51)**	1.07 (0.94, 1.22)	**1.30 (1.03, 1.63)**	1.04 (0.89,1.22)
Lag 2	1.08 (0.88, 1.33)	1.07 (0.94, 1.22)	1.13 (0.90, 1.43)	1.06 (0.90,1.23)
Lag 0-2	1.22 (0.95, 1.57)	1.10 (0.93, 1.30)	**1.37 (1.03, 1.82)**	1.04 (0.86,1.27)

The following is a list of key observations regarding the indoor component (excerpts from author's coauthored paper (O'Lenick et al. 2019):

"In general, positive and significant odds ratios (OR) were observed between health outcomes and indoor heat, particularly for 3-day moving averages, when health outcomes were defined using mortality data compared to hospital admissions (HA) data.

ORs between circulatory and heat-related mortality and maximum indoor WBGT were statistically significant and large relative to the magnitude of typical ORs *between ambient temperature and health, suggesting a considerable increase in the odds of death due to exposure to high indoor heat. Associations between respiratory mortality and morbidity and all metrics of indoor thermal comfort were weak and non-significant. When comparing indoor exposure metrics, indoor WBGT (and DI, which is highly correlated with it) tended to result in stronger associations compared to exposure metrics based on indoor dry-bulb temperature. Significant differences in ORs between White and African American strata were observed at the 0.05 level for heat-related events that combined mortality and HA data. No statistical evidence was found that subject sex (male versus female) or advanced age. For heat-related mortality and HAs, likelihood ratio tests (LRT) were statistically significant when comparing models that included indoor maximum WBGT (primary models) to models that only included ambient maximum temperature and ambient maximum dew point, and when comparing primary models with models that included an interaction term between ambient maximum temperature and percentage of census block group residential buildings without AC as a proxy for indoor heat exposure. Overall, the findings from the LRTs highlight the added value that estimates of indoor heat exposure with temporal variation offer over more commonly used modeling approaches."*

3. INDOOR EXPOSURE TO HEAT IN THE AGE OF MECHANICAL AC

In this chapter, indoor exposure to heat in residential buildings and scenarios where an AC system is present but is not functioning properly are investigated. In addition, the author identifies how different building characteristics can mitigate or intensify indoor overheating and investigates the sensitivity of indoor environment to ambient temperature in the face of climate change. Physics-based models of buildings were used to simulate indoor thermal conditions with fully-functional AC, without any type of AC, with inadequate cooling (see Section 3.1.3 for definition), and under power outages. Phoenix, Houston, and Los Angeles were selected as testbeds for a framework that can also be applied to other cities with high prevalence of residential AC. The simulations were supplemented by data from a heat-vulnerability survey to provide estimates of vulnerable population size exposed to each exposure category. Throughout the chapter, contributions from other researchers is acknowledged as appropriate in footnotes.

3.1. Methods

Whole-building simulations of archetypical residential buildings were used to assess indoor overheating under different AC availability scenarios. To account for uncertainties in input, a parameter tree (Section 3-1-2) was created that included many possible combinations of building characteristics. In addition, the heat-vulnerability survey (Section 3-1-4) was used to estimate the number of people aged 65 and older exposed to each category of AC availability.

3.1.1. Selected cities

Phoenix, Houston and Los Angeles are large cities in the Sun Belt of the US. With an urban population of 4,737,270, Phoenix is located in the northern reaches of the Sonoran Desert and has a hot/dry climate, with occasional monsoonal weather patterns during the summer. In general, around 97% of residential buildings in Phoenix have some type of AC, with more than 90% having central air units (USCB 2017). Los Angeles is located along the Pacific Ocean in the western edge of the country and has an urban population of 12,150,996. The inland regions of the city fall in the Csa (Mediterranean with hot summers) category of Köppen–Geiger climate classification system. The overall AC prevalence in the Los Angeles metropolitan area is 77%, with 54% of homes having central AC systems (USCB 2017). Houston (Urban pop. = 4,944,332) is located on the gulf coastal plain, with a climate characterized as humid subtropical (Cfa in Köppen–Geiger system). It has hot humid summers and mild winters. Therefore, similar to Phoenix, more than 90% of homes in Houston have central air conditioning (USCB 2017).

All three cities have large populations, and relatively similar building stock. Meanwhile, the difference in their climates and AC prevalence provides enough variability to isolate impacts of these two important factors. Hence, they were selected as case studies in the analysis.

3.1.2. Whole-building energy simulations

Based on the same justification as in Section 2-2-1-1, EnergyPlus was selected as the simulation tool to model indoor thermal conditions under different scenarios. In addition, the same heat metric (WBGT) and threshold (23˚C) was used here (see Section 2-1-1-2). Moreover, based on the same argument in Section 2-2-1-1, instead of modelling any specific building, the author relied on archetypical buildings that represent the building stock in each city. Based on the heat vulnerability survey (see Section 3-1-3), the majority of residential units (73% in Los Angles, and 83% in Phoenix, and 76% in Houston) in all three cities are detached single-family units. Notably, this fraction is even higher among the elderly in both cities (USCB 2017). Hence, the analysis was limited to this type of building.

Figure 13 shows the parameter tree that was created to account for numerous uncertainties in the input (in particular, variables that determine indoor thermal conditions). Comparing different sub-sets of this parameter tree helps identify how different building characteristics affect the overheating outcome in each location. In total, 59,904 simulations (with 15-minute time steps) were run for each city. Variables not included in the parameter three are identical across all archetypes and are set based on Building America House Simulation Protocols developed by National Renewable Energy Laboratory of U.S. DOE (Hendron and Engebrecht 2010).

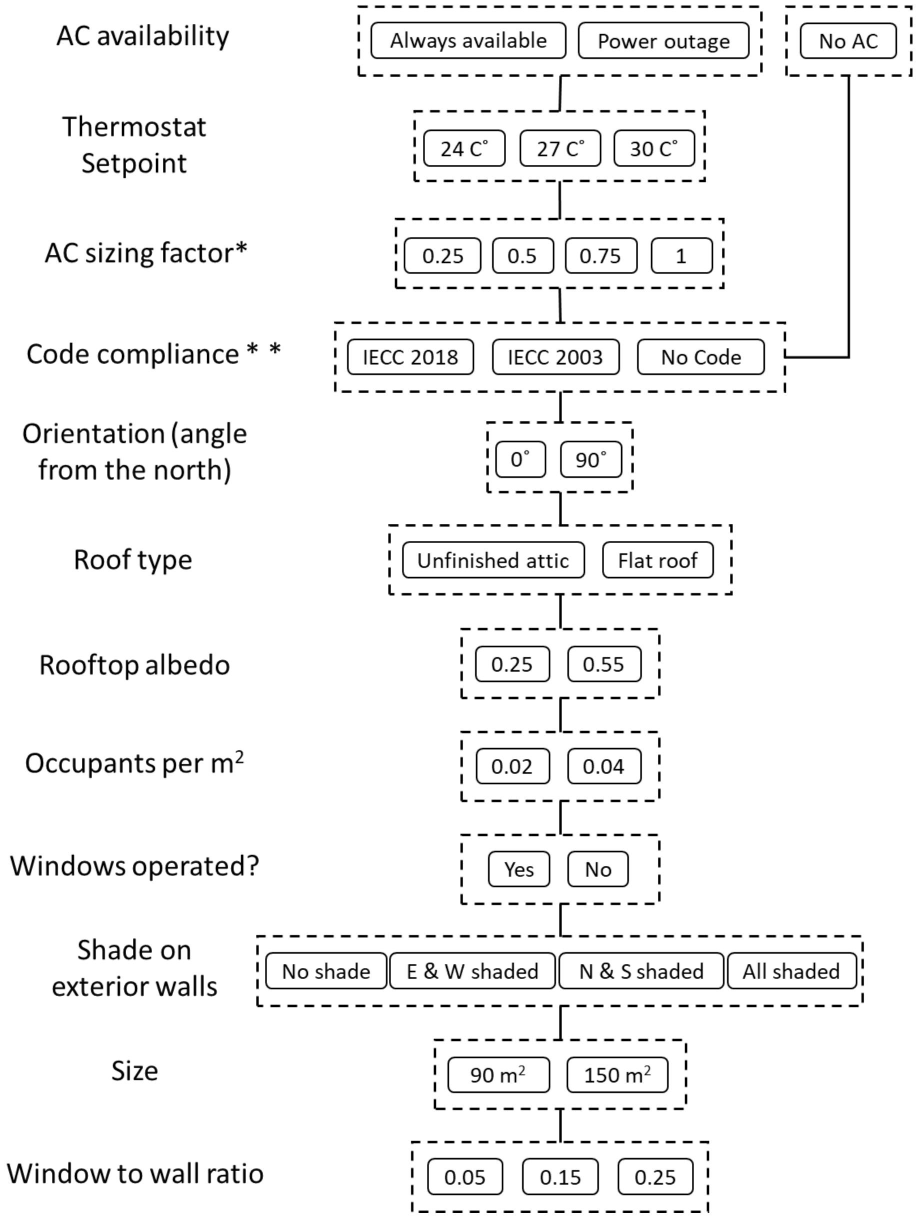


*Figure 14. Simulation variables parameter tree. * see Section 3-1-2-1 for definition. ** Code compliance determines envelope thermal properties. This includes the level of insulation in exterior walls, ceiling, and the floor, as well as air exchange rate and window properties (heat gain coefficient and u-value).*

While this parameter tree does not include thermal mass (e.g., load-bearing walls made of brick or concrete blocks), it is well-documented that buildings with thermal mass show a different thermal behavior than wood-frame buildings. Nevertheless, the parameter tree was limited to wood-frame buildings because it has been (and continues to be) the most common wall construction type in all three cities since 1970's primarily because of cost (Bradtmueller et al., 2014). Due to the costs, a return to traditional thermal mass (brick and concrete block) in typical residential buildings is unlikely. Therefore, this sample also represents buildings that will be built in near to mid future (In specific, the subset that is compliant to the newest energy code). However, if phase change material technology (a surrogate for traditional thermal mass) becomes economically feasible, it can significantly change the passive performance of buildings. In (Baniassadi et al., 2019a), the author analyzed the potential impacts of PCM's on indoor heat in residential buildings.

3.1.2.1. Modelling AC non-functionality and establishing terminology

As shown in the parameter tree, and based on data from previous studies (Hayden, Brenkert-Smith, and Wilhelmi 2011; Hayden et al. 2017), AC availability and functionality can be categorized into the following:

1- AC system is present with no limitations on using it (i.e., proper thermostat setpoint). This can be referred to as "fully-functional AC".

2- AC system is present but is kept at a higher thermostat setpoint due to high electricity cost or decreased thermal sensation. An example is B6 in Section 2-1-2-1.

3- AC system is present but is either undersized or faulty and thus, cannot meet the desired temperature. An example is B1 in Section 2-1-2-1. The most common fault in residential AC systems is AC undercharge. Proctor (Proctor 2000) reports that only 38%

of residential cooling systems in California (sample size=4000 homes) have proper refrigerant charge. See appendix 2 for more discussion on this topic.

4- A combination of second and third categories

5- The AC system is completely turned off or is not present.

6- A power outage that results in temporary loss of AC. The difference between this category and the previous one is that the indoor temperature is comfortable at the beginning of the power outage and takes some time to approach that of “No AC” category. In addition, a significantly larger population would be implicated under this scenario.

Here, the second, third, and fourth categories are grouped together and referred to as “Inadequate Cooling”. Simulating buildings with fully functional AC, no AC, and high thermostat set-point with a whole-building energy model is straightforward as it only requires tweaking a few EnergyPlus input parameters. However, there is no direct way to model a broken (e.g., a system that leaks refrigerant) or undersized AC unit (Third category of AC functionality in the above list). As a workaround, the author proposes the use of the input parameter “SizingFactor” in EnergyPlus. At the beginning of each simulation, EnergyPlus calculates the peak cooling demand during the “Design Day” and sizes the AC system accordingly (DOE 2017). American Society of Air Conditioning and Refrigeration Engineers (ASHRAE) defines the cooling design day as the day with maximum temperatures that are exceeded only by 1% of the historic records. In this study, broken/undersized AC system was replicated by reducing the sizing factor (SF) from 1 (the default in EnergyPlus) to 0.25, 0.5, and 0.75[22]. In appendix 2, a technical summary of the conditions that can result in different SF values is provided. An initial sensitivity analysis showed that in the three cities, SF values above 0.75 lead to a performance almost similar to that of a fully functional AC. In fact, evidence (see the summary in appendix 2) suggests that unless the purchased system was significantly oversized, the post-installment cooling capacity performance of most central AC systems fall within the 0.75 – 1 range. The initial sensitivity analysis also showed that at SF values below 0.25, the AC system capacity was reduced to a degree that resulted in indoor air temperatures similar to that of the no AC scenario. An example of this scenario is the building #1 (B1) from the sample of residential buildings discussed in Section 2-1-2-1. As observed during post-measurement interviews, *"the AC system in this building was blowing air at the same temperature as the room air".* Hence, in the results presented here, the SF of broken/undersized AC systems was bounded by 0.25 and 0.75[23]. This range is in line with findings from author's review of the literature on residential AC faults and their impact on cooling capacity that shows typical AC faults

[22] Author acknowledges that AC systems are not available at all sizes. Therefore, the actual installed capacity could be different (often, slightly higher) than what is required. However, a survey of current product lines by common brands in US (Goodman, Carrier, and Trane) shows that residential systems are available with 10-20% increments in cooling capacity. Therefore, unless the installed system was deliberately oversized, author estimates that the impact of product availability on SF is less than 10%.

[23] EnergyPlus applies the part-load curves for the AC system using the nominal capacity sized during the sizing period. Here, Sizing Factor is manipulating the sizing period and thus, can introduce errors because the part-load curves will reflect a smaller system. Since the assumption is that AC was originally sized properly and then became faulty, a sensitivity analysis was conducted on a small sample of buildings in which SF values remained the same, but the part-load curves were modified to reflect the SF=1 scenario. It was found that the impacts on the results were negligible, and mostly at lower indoor temperatures (that are of no interest in this dissertation).

such as refrigeration undercharge, duct leakage, and reduced evaporator flow (due to improper duct work) can easily reduce the nominal cooling capacity by 50%. In particular, this matches the range reported by Stephans et al. (Stephens, Siegel, and Novoselac 2011) who investigated 17 residential and light-commercial AC systems in Austin, TX, and compared the measured capacity of the systems with their nominal capacity as reported by the manufacturer (see appendix 2 for more examples). The other potential cause of inadequate cooling in residential buildings is a system with insufficient cooling capacity. This is different from faulty systems and mostly happens when residents rely on small window unit systems to cool a space beyond their capacity (e.g., as a semi-permanent solution to a broken central AC that is too expensive to repair). There is no reliable data available on the prevalence of this issue. Nevertheless, from a modelling perspective, this impact can be accurately represented by the SF parameter. In fact, that is the main definition and original purpose of this input parameter in EnergyPlus.

Regarding the thermostat set-point (the other component of inadequate AC), 24 ˚C was selected as the set-point for people who have no limitations to run AC (based on data in (EIA 2015)). To mimic indoor conditions for occupants who report electricity costs as a barrier to fully utilize their AC, it was assumed that their temperature set-point is set between 27 ˚C and 30 ˚C. The lower bound was set to 27 ˚C because thermal discomfort and health impacts below this temperature are minimal based on available comfort models and epidemiology evidence (see Section 2-1-1-2). The upper bound (30

˚C) was selected based on (White-Newsome et al. 2012) and the data recorded in 46 homes in Phoenix (D. Hondula 2018).

A separate batch of simulations was run in which AC availability schedule in EnergyPlus was modified to reflect 24-hour power outages at 50^{th}, and 90^{th} percentiles of mean daily outdoor dry-bulb temperature. The period was set to a full diurnal cycle to capture effects at different times of the day. Based on the historic data, 24 hours is the 75th percentile of outage duration in 1,137 incidents that impacted at least 500,000 people between 2000 and 2016. The median in the data was around 18 hours. These metrics were calculated using the raw data in (Mukherjee, Nateghi, and Hastak 2018). During power outages, a key factor in determining the overheating outcome is the initiation time of the outage. In this study, 5 PM local time was selected as the initiation time based on two factors. First, this author's sensitivity analysis (which included all three cities Phoenix and Los Angeles) shows that 24-hour power outages initiated at 4 – 6 PM result in maximum 24-hr indoor air temperatures (Baniassadi, Sailor, and Bryan 2019). Second, 5 PM is within the summertime peak electricity demand hours (3 - 9 PM) which is a more likely period for power outages induced by electricity infrastructure overload. Based on the author's analysis of the data in (Mukherjee, Nateghi, and Hastak 2018), 25% of power outages (from all causes) affecting more than 500,000 people between 2000 and 2016 happened in the 4 PM – 6 PM window.

3.1.2.2. Weather data

In the building science literature, researchers often use Typical Meteorological Year (TMY) data that is provided by U.S. Department of Energy. TMY data is generated based on historic records and represents a typical year. In this study, version 3 of the TMY data (TMY3) was used. Phoenix Sky Harbor Airport (Phoenix), George Bush Intercontinental Airport (Houston), and the California Climate Zone 9 (Los Angeles) are the representative weather stations. To assess the sensitivity of indoor thermal conditions on ambient temperatures (as a proxy for the impacts of climate change and urban heat), days in the TMY3 data were ranked based on daily mean temperature; and days at 50th, and 90th percentile in each city were selected for further analysis.

Table 3. Basic climate data of the three cities (June – Aug)

City	24-hr average ambient dry-bulb temperature (˚C)					Average relative humidity (%)
	Minimum	Maximum	Mean	50th PCTL	90th PCTL	
Los Angeles	15.4	27.6	21.3	21.4	25.4	75.0
Phoenix	18.1	38.3	32.5	32.7	37.2	26.7
Houston	19.2	31.9	27.0	27.4	29.7	74.8

As the weather records show, the three climates are very distinct; thus, provide enough variability in the analysis.

3.1.3. Heat-vulnerability survey and population estimates

The heat vulnerability was conducted to better understand how people aged 65 and older living in Phoenix, Los Angeles, and Houston are affected by extreme heat. The phone survey was implemented from August 22, 2017 to Sept. 20, 2017. The survey was conducted in both English and Spanish. The target sample for this survey was Phoenix and Los Angeles residents 65 and over. A Random sample (without replacement) of all landline and cell phones of households with a high likelihood of having an adult aged 65 years or older, randomly distributed across the population of the study cities was performed. During calling, respondent race and ethnicity was monitored in order to ensure the distribution of completes was comparable to the population of older adults in the three cities. The number of survey respondents was 306, 303, and 305, in Los Angeles, Phoenix, and Houston, respectively. The overall sampling error was 5.60%, for Los Angeles, 5.62% for Phoenix, and 5.60% for Houston (all at a 95% confidence level). For this survey, the margin of error calculation used the commonly accepted value of ±5%, a 95% confidence interval, maximum variation (i.e., 50/50), and an estimated population of 437,224 in Los Angeles, 142,548 in Phoenix, and 196,359in Houston (residents aged 65 years and older). The survey was consisted of 31 heat-related and 14 demographic questions. However, this analysis relied on cross-tabulation among only a subset of questions to estimate the population size in each AC functionality category[24]. After filtering out samples that lived in a building other than single-family detached buildings as well as those who would leave their home if it felt too hot, the remaining respondents were separated based on their response to the question about their AC system. It was assumed that respondents who did not have any type of mechanical (central and/or window units) or evaporative cooling are exposed to the thermal conditions that match the “No AC” category from the simulation set. Then, the group

[24] Author acknowledges help and support from Dr. Cassandra O’lenick (NCAR) in this part

who “felt too hot inside their homes” and/or had heat-related symptoms despite having at least one of the mentioned systems was assigned to the “Inadequate Cooling” category. The remaining group (respondents who had at least one of the mentioned systems and did not “feel too hot” or experience heat-related symptoms) were assigned to the “Functional AC” category (TS= 23 ˚C and SF=1). For the power outage scenario, the fraction of the population exposed to conditions under the “power outage” simulations were assumed to be the same as the fraction who did not leave their home when they “felt too hot” and/or experienced symptoms of heat. Finally, the population size associated with each AC functionality category was estimated by applying the fractions from the survey sample to the total population aged 65 and older in each city. Figure 15 shows the estimated population size of each group. These values are also reported in the associated figures throughout the chapter.

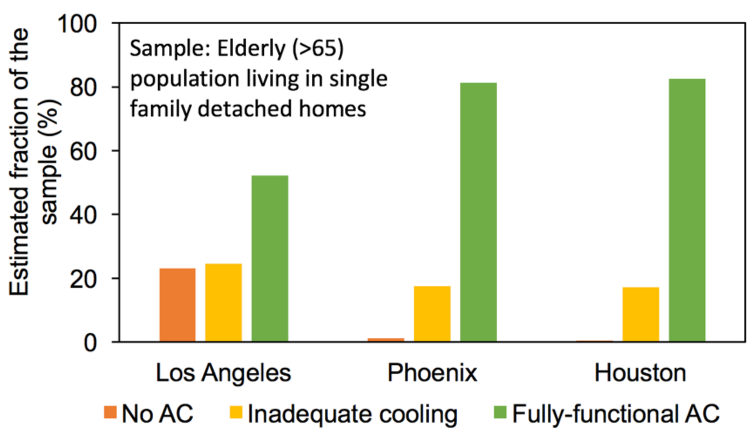


Figure 15. Estimated fraction of population associated with each AC category.

The survey did not include a question regarding exterior wall type. Therefore, we could not filter out the respondents who lived in homes with thermal mass and had to assume that there is no considerable codependency between exterior wall type and AC functionality. In other words, we assumed that the fractions shown in Figure 15 would be roughly same for the subset of buildings that we modelled (wood-frame). It also noteworthy that in general, assessing the exterior wall of buildings for modeling purposes is challenging because individual homeowners or tax assessors often report the most external layer (that is visible from outside), which might not be indicative of the primary wall construction (e.g., stucco).

3.2. Results and discussion

3.2.1. Indoor heat and AC functionality

Figure 16 shows the cumulative distribution of WBGT inside the simulated building set under the “No AC” and “Fully-Functional AC” scenarios for the period of June-Aug. The vertical axis in these figures (and those similar to it that follow) shows the cumulative fraction of hours at or below the associated WBGT. For example, if the curve shows 0.4 at WBGT of 25 ˚C, it means that WBGT is below 25 ˚C for 40% of the times. Here, (and henceforth in this chapter) fully functional AC refers to a sizing factor (SF) of 1 and a thermostat set-point (TS) of 24 ˚C. The black solid line shows the average conditions while the dashed colored lines show the conditions inside buildings with 10^{th} (blue) and 90^{th} (red) percentiles of WBGT. Hence, the higher the difference between the dashed lines, the more variation among buildings, and the more significant the role of building characteristics in determining the indoor overheating outcome. To represent the current building stock, buildings compliant to the 2018 IECC code are excluded from this figure.

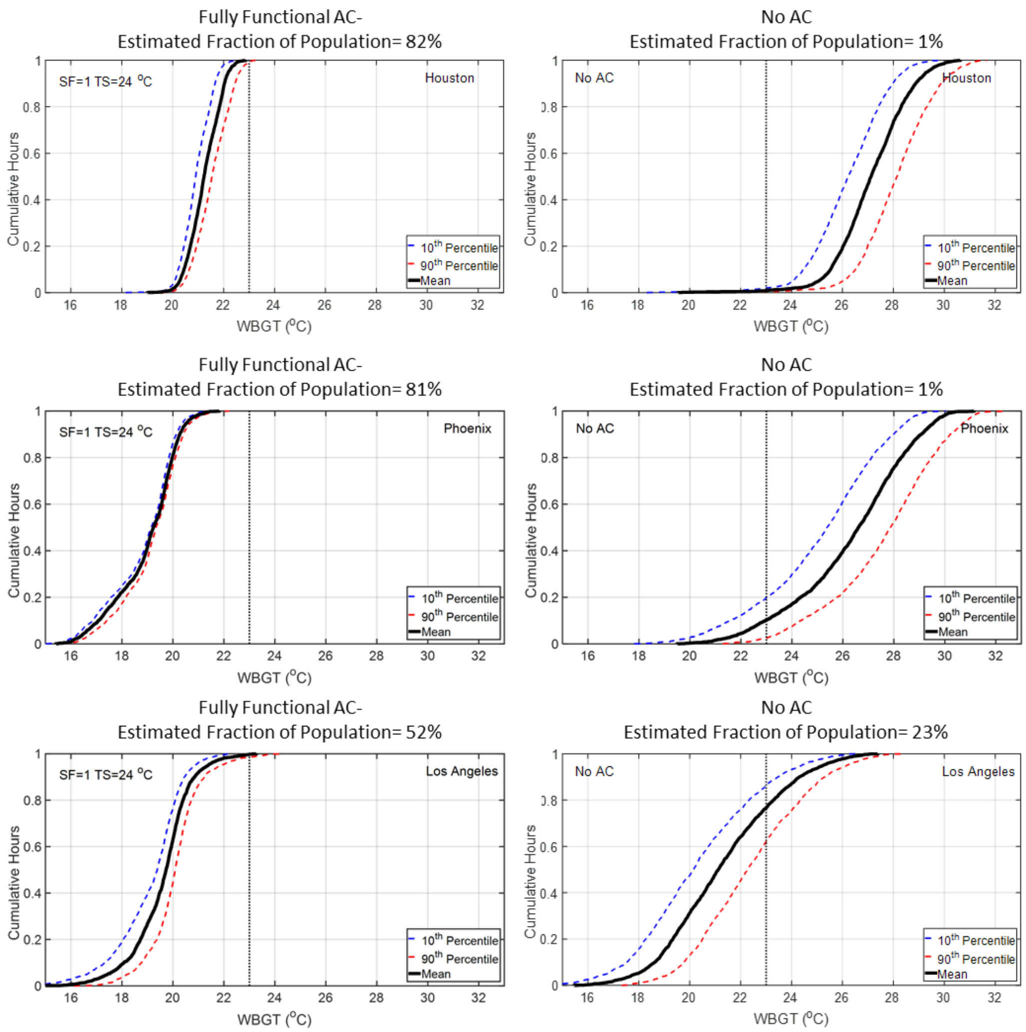
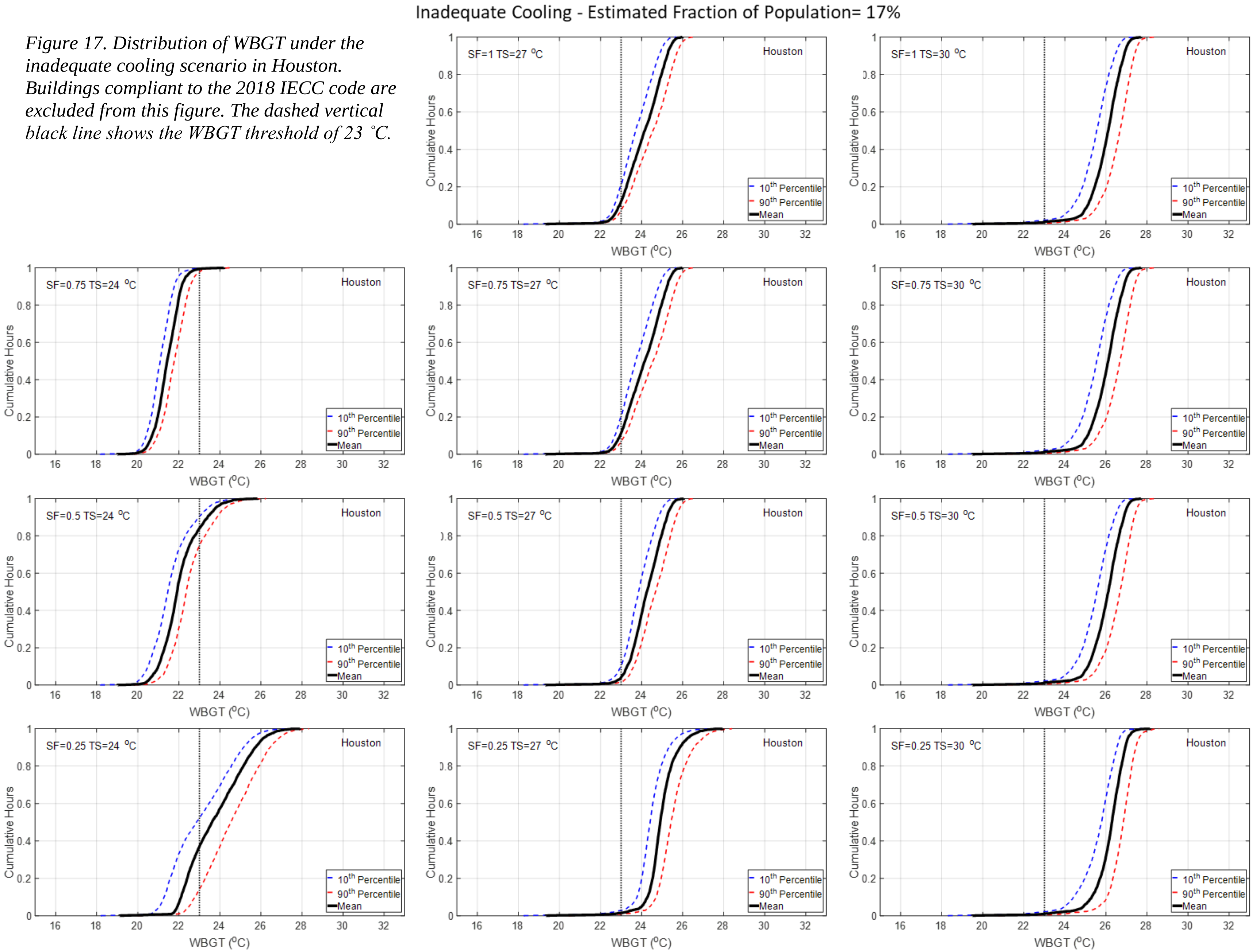


Figure 16. cumulative distribution of WBGT (June-Aug) inside the simulated building set under the No AC and Fully-Functional AC Scenarios. Buildings compliant to the 2018 IECC code are excluded from this figure. The dashed vertical black line shows the WBGT threshold of 23 ˚C.

As this figure suggests, a working AC with a proper thermostat set-point guarantees comfortable thermal conditions and prevents buildings from overheating at all times in all cities. In addition, under this scenario, the difference caused by building characteristics is small. In other words, as long as there is enough cooling capacity and it is set at proper thermostat temperature, no overheating occurs. On the other hand, in the absence of mechanical cooling, indoor thermal conditions become highly dependent on climate and building characteristics. In Phoenix and Houston, an unconditioned residential building will stay above the WBGT threshold of 23 ˚C at almost all the times during the June-Aug period, with significant variations caused by different building characteristics (note the difference between 10^{th} and 90^{th} percentile lines). Notably, this is inversely correlated with the number of people who don't have any type of cooling, which is around 1% in both cities, meaning that only a small subset of people is exposed to this level of indoor heat. Conversely, in Los Angeles, where the indoor thermal conditions without AC is more moderate (on average, WBGT is below the threshold 80% of times), 23% of the population fall in this category.

Figures 17-19 show the same distribution under the inadequate cooling category, categorized by different combinations of sizing factor (SF) and thermostat setpoint (TS). Again, to represent the current building stock, buildings compliant to the 2018 IECC code are excluded from these figures.

Figure 17. Distribution of WBGT under the inadequate cooling scenario in Houston. Buildings compliant to the 2018 IECC code are excluded from this figure. The dashed vertical black line shows the WBGT threshold of 23 ˚C.



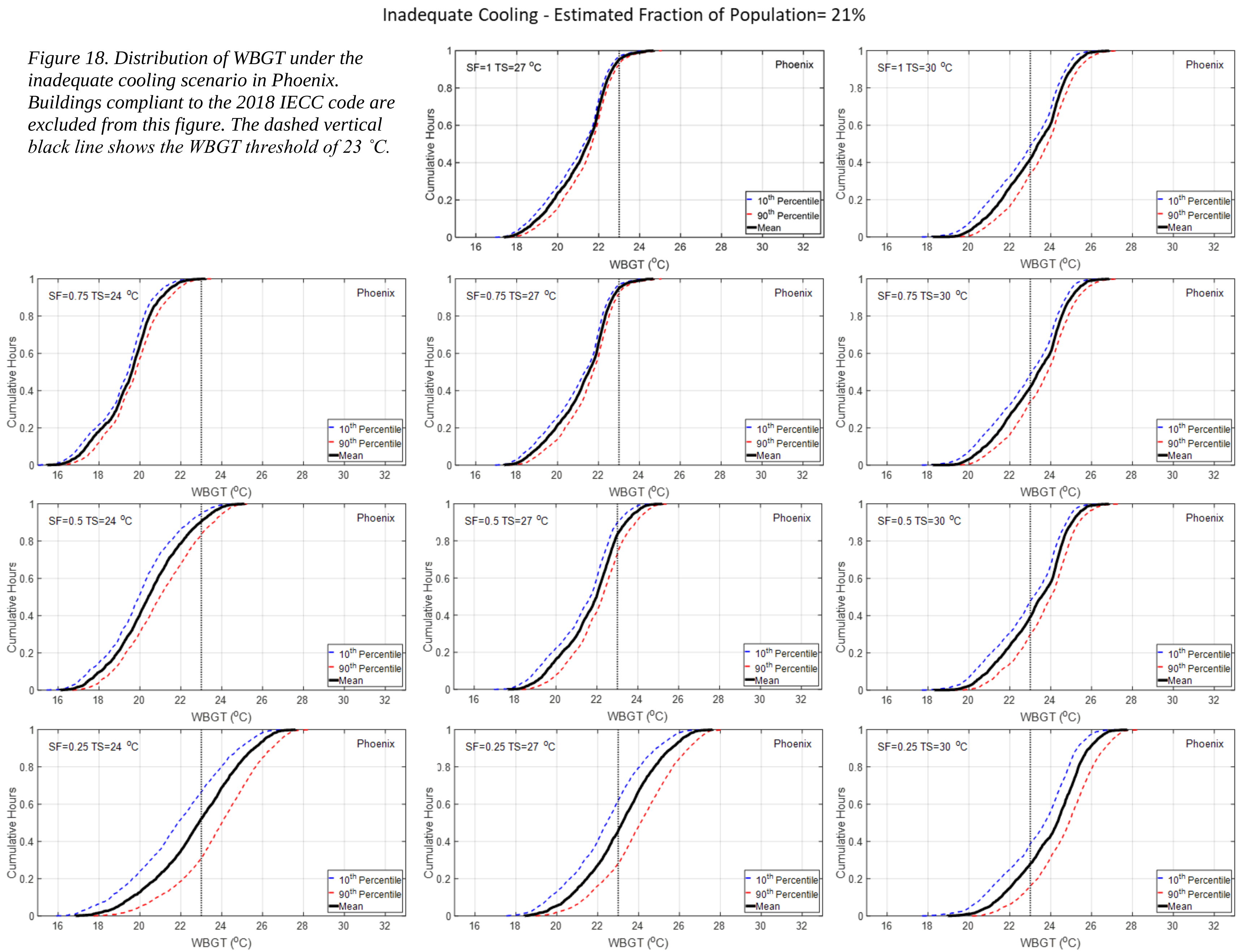
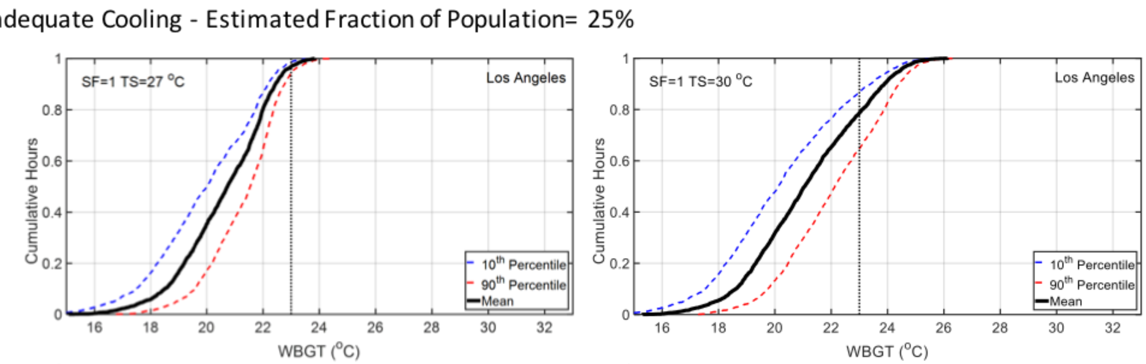
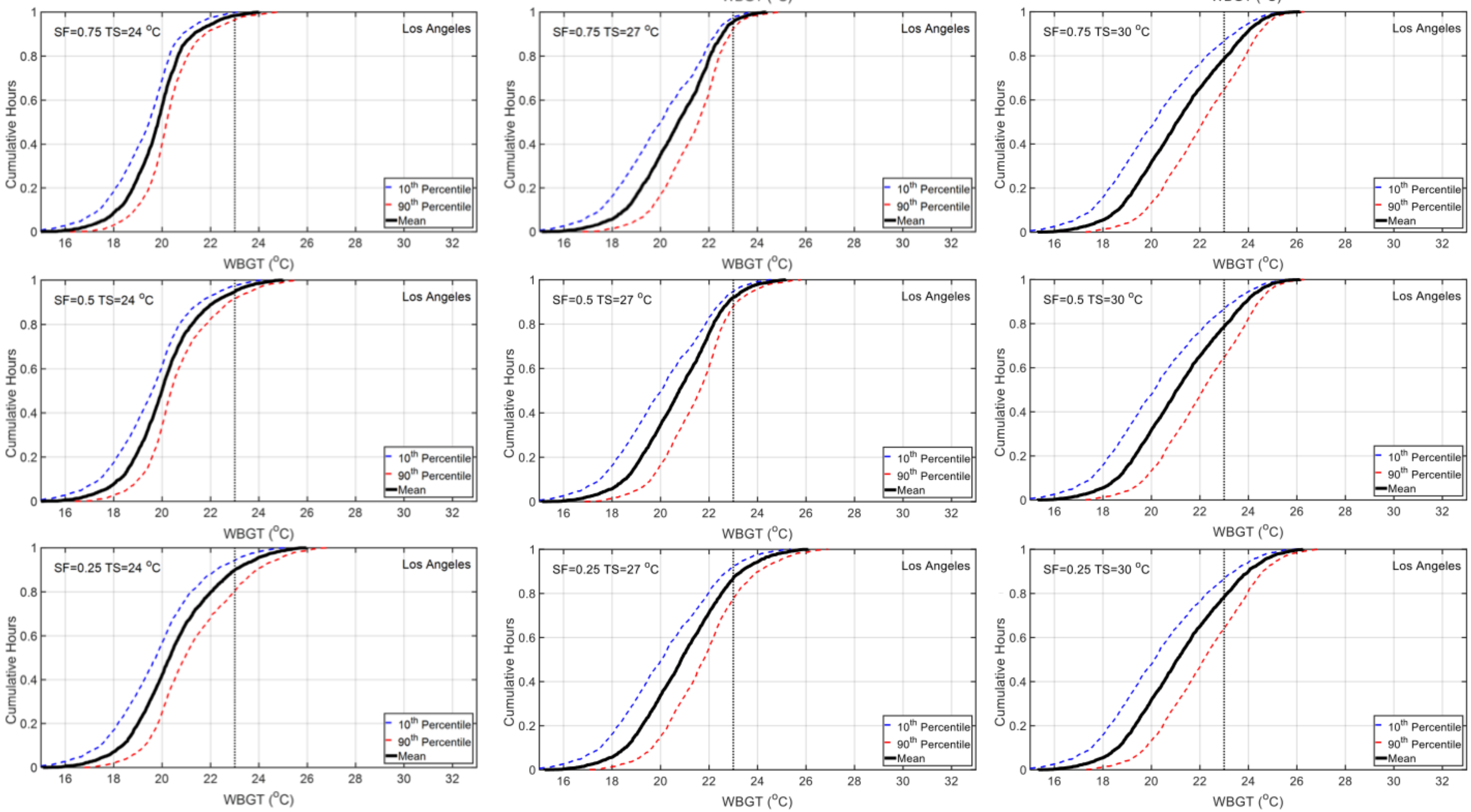


Figure 18. Distribution of WBGT under the inadequate cooling scenario in Phoenix. Buildings compliant to the 2018 IECC code are excluded from this figure. The dashed vertical black line shows the WBGT threshold of 23 ˚C.

Figure 19. Distribution of WBGT under the inadequate cooling scenario in Los Angeles. Buildings compliant to the 2018 IECC code are excluded from this figure. The dashed vertical black line shows the WBGT threshold of 23 ˚C.





As the data suggests, the level of cooling inadequacy (as defined by TS and SF) significantly impacts the indoor conditions for the population that falls in this category. It is also highly dependent on climate characteristics. Nevertheless, the distinction between the fully functional AC scenario of figure 16 and most of the inadequate cooling scenarios of figures 17-19 clearly highlights the importance of not considering AC as a binary variable. Especially, since the size of the population that falls in this category is considerable (17% in Houston, 18% in Phoenix, and 25% in Los Angeles). Figure 20 is a simplified demonstration of the effect of TS and SF on the average indoor thermal conditions inside residential buildings (June – Aug).

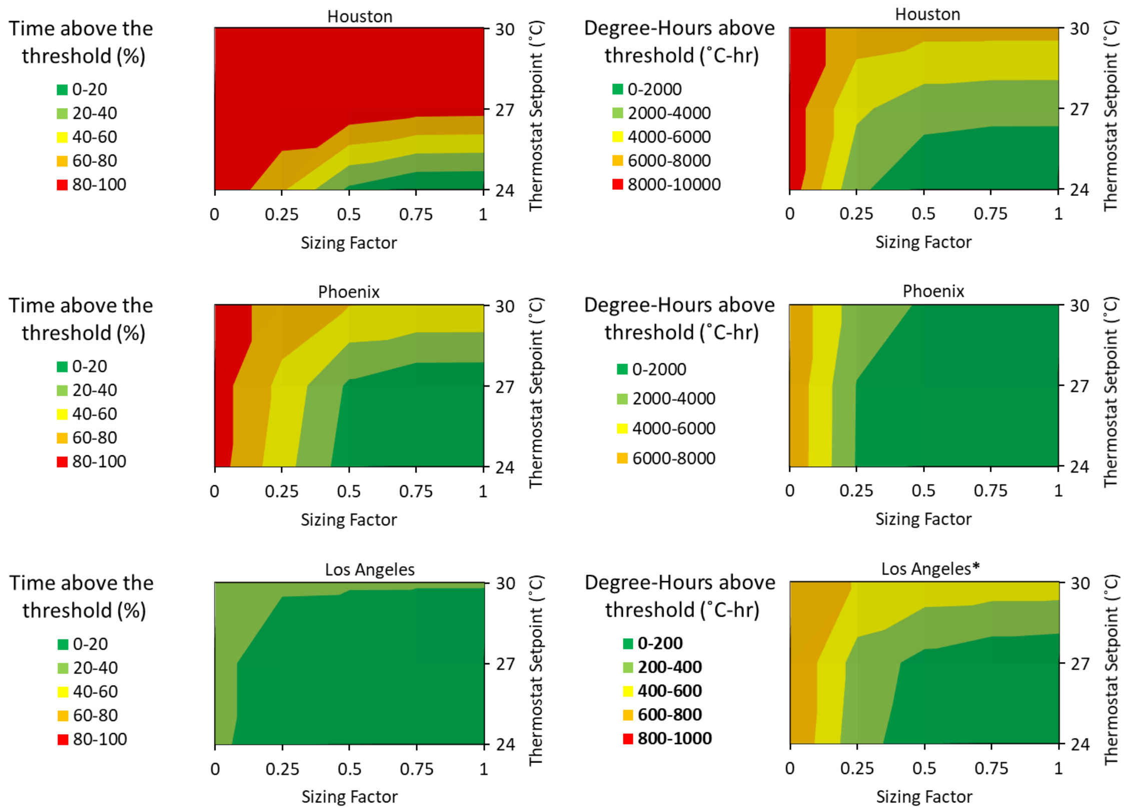


*Figure 20. Average duration (time above threshold) and intensity (degree-hour above threshold) of overheating inside residential buildings as a function of AC sizing factor (SF) and (TS). Buildings compliant to the 2018 IECC code are excluded from this figure. * note the different scale for Los Angeles.*

Again, data presented here highlights the sensitivity of indoor conditions to operation parameters (TS and SF) of AC, as well as the significant impact of the underlying climate (note the different scale in for Los Angeles). In addition, it shows that the relative impact of TS and SF is a function of climate characteristics; namely, the humidity. In Phoenix, an AC system working at half the required capacity can keep the thermal conditions below the threshold for more than 80% of the time when set to a 27 ˚C thermostat setpoint. The same set of parameters in Houston leads to thermal conditions that **exceeds** the threshold for more than 80% of times.

According to the survey result, the main purpose of increasing thermostat setpoint is to save on electricity[25]. Therefore, to provide context for the presented data, Figure 21 shows the sensitivity of AC electricity demand (June-Aug) to thermostat setpoint. The assumed system type across all simulations is central cooling air, and the efficiency is set to the IECC2003 requirements.

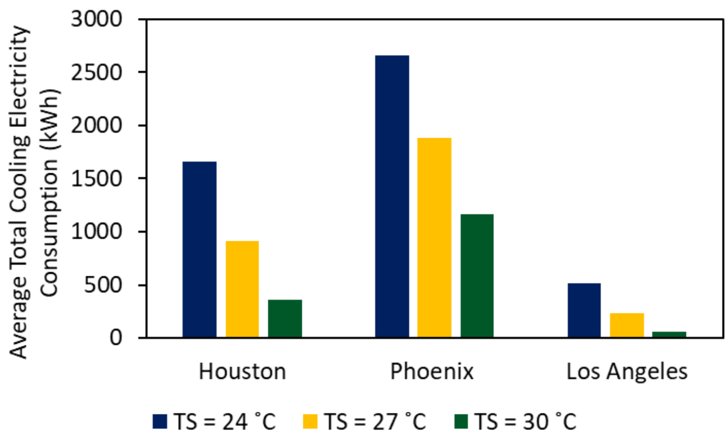


Figure 21. Sensitivity of AC electricity demand (June - Aug) to indoor thermostat setpoint. This is limited to SF of 1. Buildings compliant to the 2018 IECC code are excluded.

As these data suggest, summertime cooling electricity use is highly dependent on TS, implicating income as an underlying component of AC inadequacy to heat in the three cities.

[25] Although, a small subset of samples cited non-financial concerns such as environmental issues. In the survey, around 60% of people who reported that some factor prevents them from using AC appropriately in Phoenix and Los Angeles cited concerns about electricity cost. This was more than 80% in Houston.

3.2.2. Sensitivity to ambient temperature and role of power outages

Figure 22 presents WBGT inside buildings at days with 50th and 90th percentiles of outdoor dry-bulb temperature (The horizontal axis). Each boxplot in this figure contains hourly WBGT data inside all buildings (24 data points for each building) that fall into the associated AC functionality category (IECC 2018 was excluded from the sample). Henceforth, inadequate cooling is defined by TS values of 24 - 30℃ and SF values of 0.25 - 0.75. To make sure the times windows are consistent and comparable, the 24-hour period across all categories was set to 5 PM to 5 PM (next day) to account for the fact that the power outage scenario starts and ends at this hour.

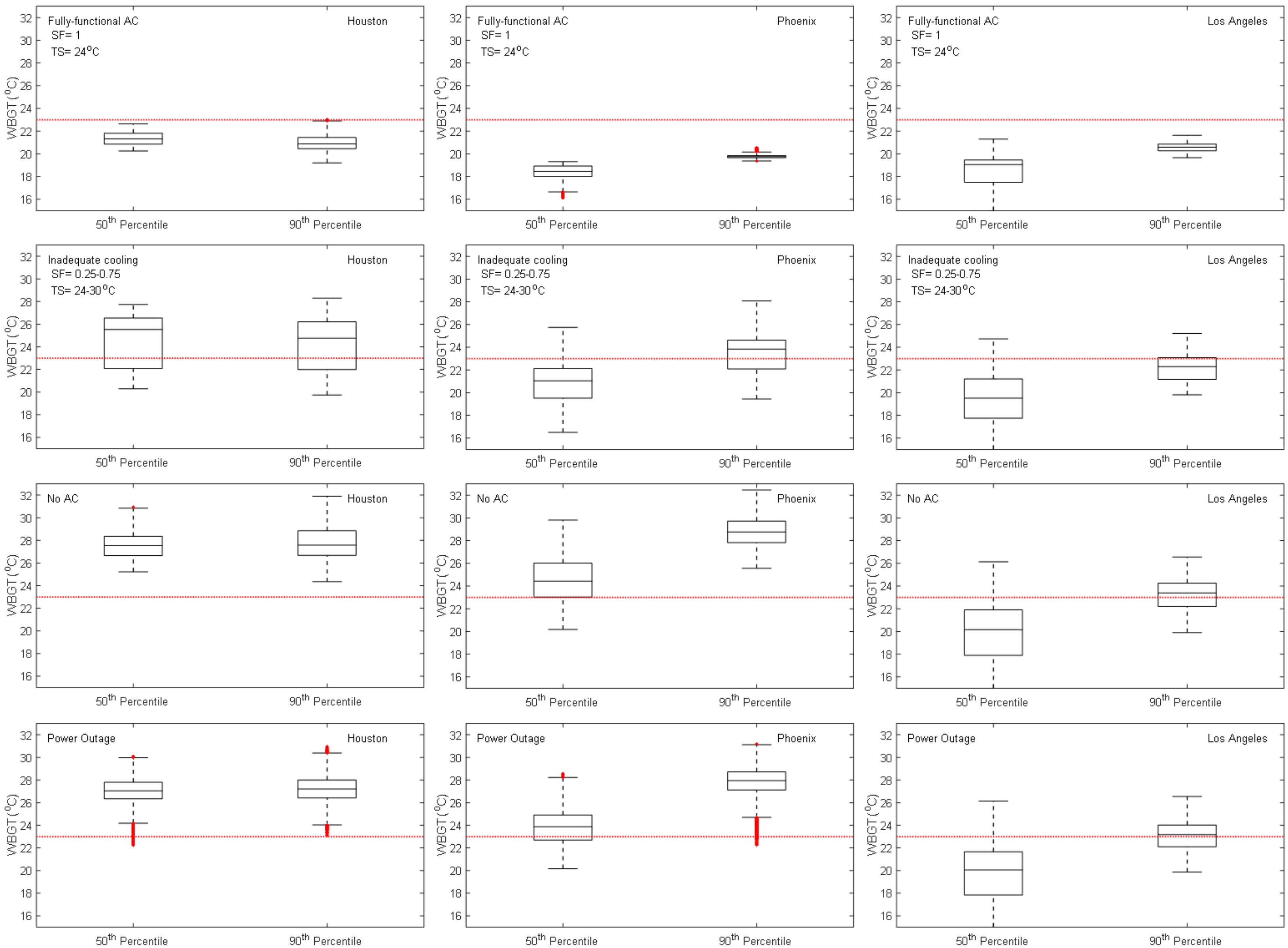


Figure 22. WBGT inside buildings at days with 50th and 90th percentiles of outdoor dry-bulb temperature (The horizontal axis). Each boxplot in this figure contains hourly WBGT data inside all buildings that fall into the associated AC functionality category (IECC 2018 was excluded from the sample). The dashed horizontal red line shows the WBGT threshold of 23 ˚C.

In addition, figure 23 shows the average increase in indoor WBGT per 1℃ increase in ambient dry-bulb temperature which was calculated using the differences at 50th and 90th percentiles of outdoor.

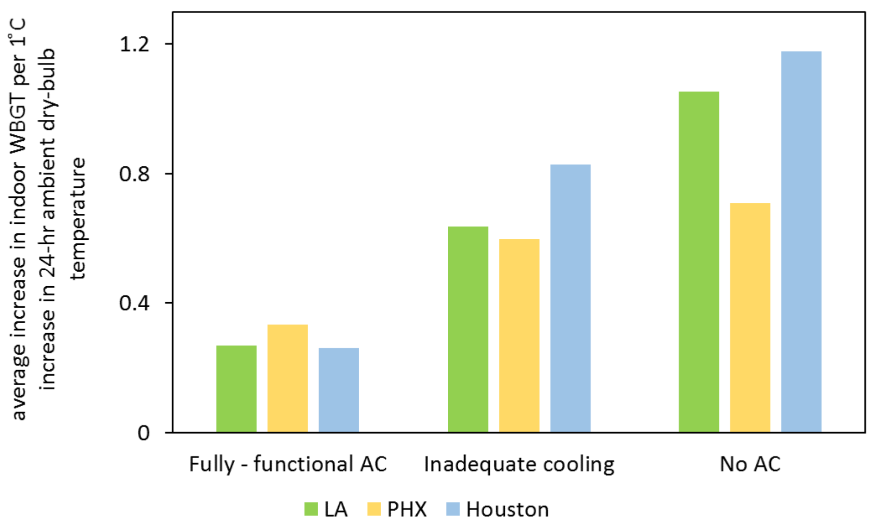


Figure 23. The average increase in indoor WBGT per 1℃ increase in ambient dry-bulb temperature (IECC 2018 was excluded from the sample).

Expectedly, the impacts of outdoor air temperature on indoor thermal conditions depends on AC-functionality. At the lower end, a fully-functional (TS= 24℃ SF=1) AC results in consistently comfortable conditions at both days in all three cities. At the higher end, under the "No AC" and "power outage" scenario, average daily indoor WBGT at the day with the 90th percentile of ambient temperature is 3-5℃ higher than that at the 50th percentile in Phoenix and Los Angeles. Assuming the associations between indoor heat exposure and health outcomes (derived in Section 2-2-2) are applicable for residents of Phoenix and Los Angeles, data presented here suggests that except for the fully-functional AC, the difference in the number of circularity implications, heat-related mortality and hospital admission at 50th and 90th percentile of ambient daily temperature is statistically significant. Based on data in Figure 15, the author estimates that this applies to 50 and 20% of the elderly population in Los Angeles and Phoenix, respectively. In Houston, because of the key role of relative humidity, while indoor WBGT has a similar sensitivity to ambient temperature as the other two cities (Figure 23), the difference in indoor WBGT at 50th and 90th percentile of ambient daily temperature is less considerable.

The other important observation is the difference between AC functionality groups at the same day. In Phoenix and Houston, the difference between “fully functional AC” and “inadequate AC”, and the difference between the “inadequate AC” and “No AC” is large enough to cause statistically significant health-outcomes (based on associations presented in Section 2-2-2). These differences are considerably smaller in Los Angeles, meaning that AC functionality and energy poverty (that are highly correlated with socio-economic aspects of vulnerability) are more important factors in Phoenix and Houston.

The slight difference (<1℃ on average) between the power outage and the No AC scenarios is due to the time it takes for indoor temperatures to rise once the power goes out. In (Baniassadi and Sailor 2018) and (David J Sailor et al. 2019), this author used simulations of archetypical residential buildings in the three cities and found out that during the hottest period in TMY3 data, typical buildings (single family detached buildings and top floor units in a multi-family apartment) take 4 – 6 hours to overheat. Based on the survey, it can be estimated that during a large-scale city-wide outage, the number of people exposed to these scenarios will be significantly higher than those exposed to the “No AC” scenario. In Los Angeles, 230,854 people can be exposed to the power outage scenario, which is 3 times higher than the number of people who do not have AC. This ratio is 52 and 161 in Phoenix and Houston, respectively. Hence, power outages have the highest potential of adverse health impacts based on both the intensity and scope of exposure.

The other notable point from this data is the possible implications of a warming urban climate. Despite differences in future projections, they all converge on the fact that the frequency of heat events across the US will likely increase as a result of climate change (Gao et al. 2012; Ebi and Meehl 2007). For example, this author’s analysis of the data from simulations by Krayenhoff et al. (Krayenhoff et al. 2018) shows that under RCP 8.5 scenario, the distribution of summertime ambient temperatures in Phoenix might shift by up to 25% by mid-century. By mapping[26] this projection into the data presented in Figure 23, it can be estimated that by mid-century, an average building in the inadequate cooling scenario would exceed the WBGT threshold in around 30% of the hours during the summer.

[26] The author acknowledges the significant discrepancies between projections (due to different assumptions, GCM models, …) and thus, refrains from providing detailed projections based on a single modelling work. See chapter 4 for more discussion on this limitation. Although, in (Baniassadi et al. 2019), this author used the mentioned data from Krayenhoff et al. and simulated indoor temperature in non-conditioned residential buildings at the start and middle of the century across eight US cities.

3.2.3. Impacts from building characteristics

In this Section, WBGT data from different subsets of buildings are compared in order to identify impacts from certain building characteristics. In particular, the impacts of developing building energy codes are of interest, because they are the most reliable surrogates for how the building stock is changing. Hence, the first comparison is between buildings compliant with 2003 and 2018 (in figures, referred to as new code (N.C.)) versions of the IECC code. In addition, to identify the mitigation potential of non-deep retrofit interventions that are not currently addressed by codes, the baseline set is compared to a subset named "Passive Strategies" (PS) which includes shaded exterior walls (e.g. by tress), a high albedo rooftop, and operable windows[27]. These strategies were added to both energy code versions. To demonstrate the differences between the compared sets, Figure 24 shows their associated parametric trees. Here, the impacts from codes are reported as the collective effect of several properties. In (Baniassadi and Sailor 2018), the author conducted a detailed analysis of individual properties (including roof and wall insulation, roof albedo, and air exchange rate) and their impacts on building performance under the hottest three-day period of the year in Phoenix and Houston. In addition, in (Baniassadi, Sailor, and Bryan 2019), he investigated the role of thermal mass (in the form of Phase Change Materials) across all three cities. Finally, in

[27] It was assumed that occupants open the windows when outdoor dry-bulb temperature is at least 2 ˚C cooler than the indoor air.

(Baniassadi et al. 2018) and (Baniassadi, Sailor, and Ban-Weiss 2019), the author explored the impacts from rooftop albedo.

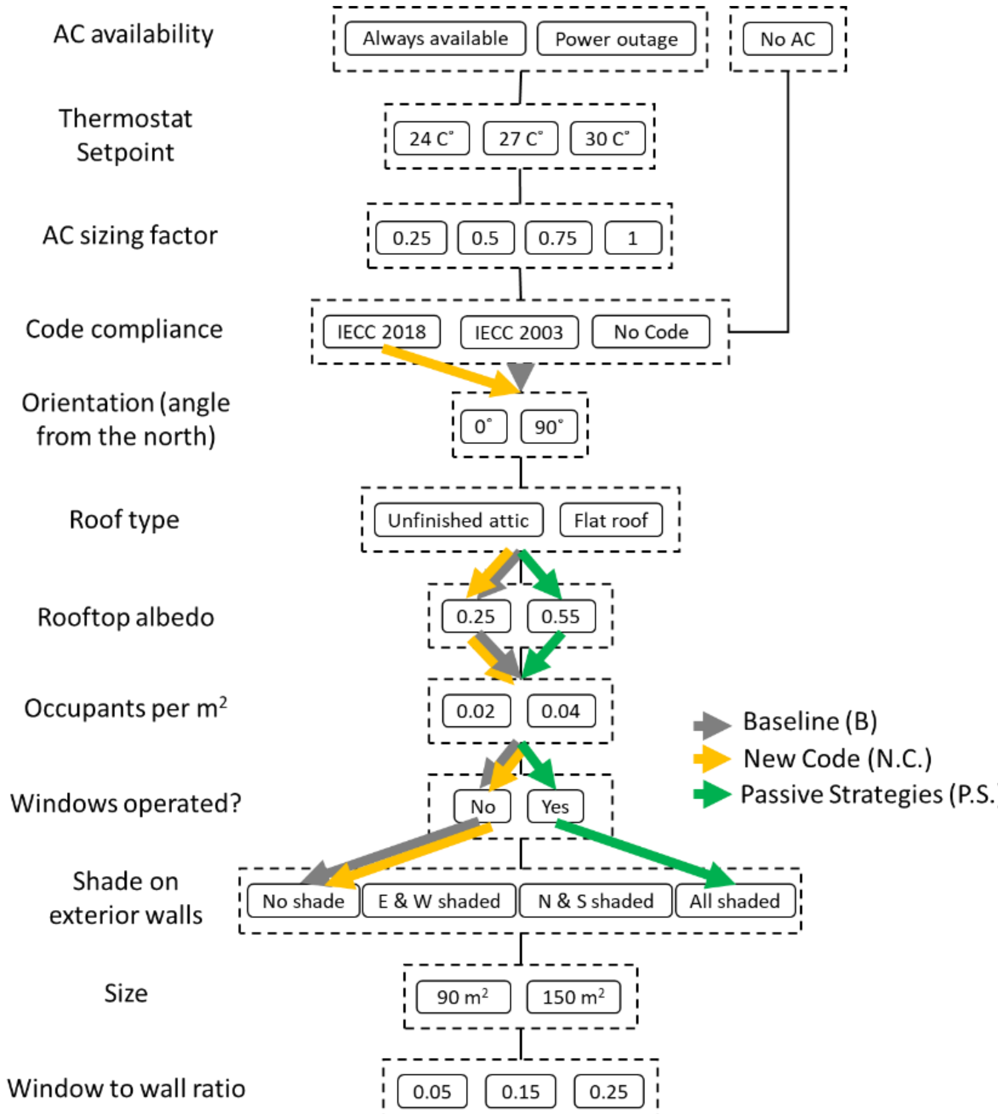


Figure 24. Parameter trees associated with permutations presented in figure 25.

The WBGT data from these permutations are compared in Figure 25. The format (in particular the, definition of the vertical axis) is similar to Figure 22.

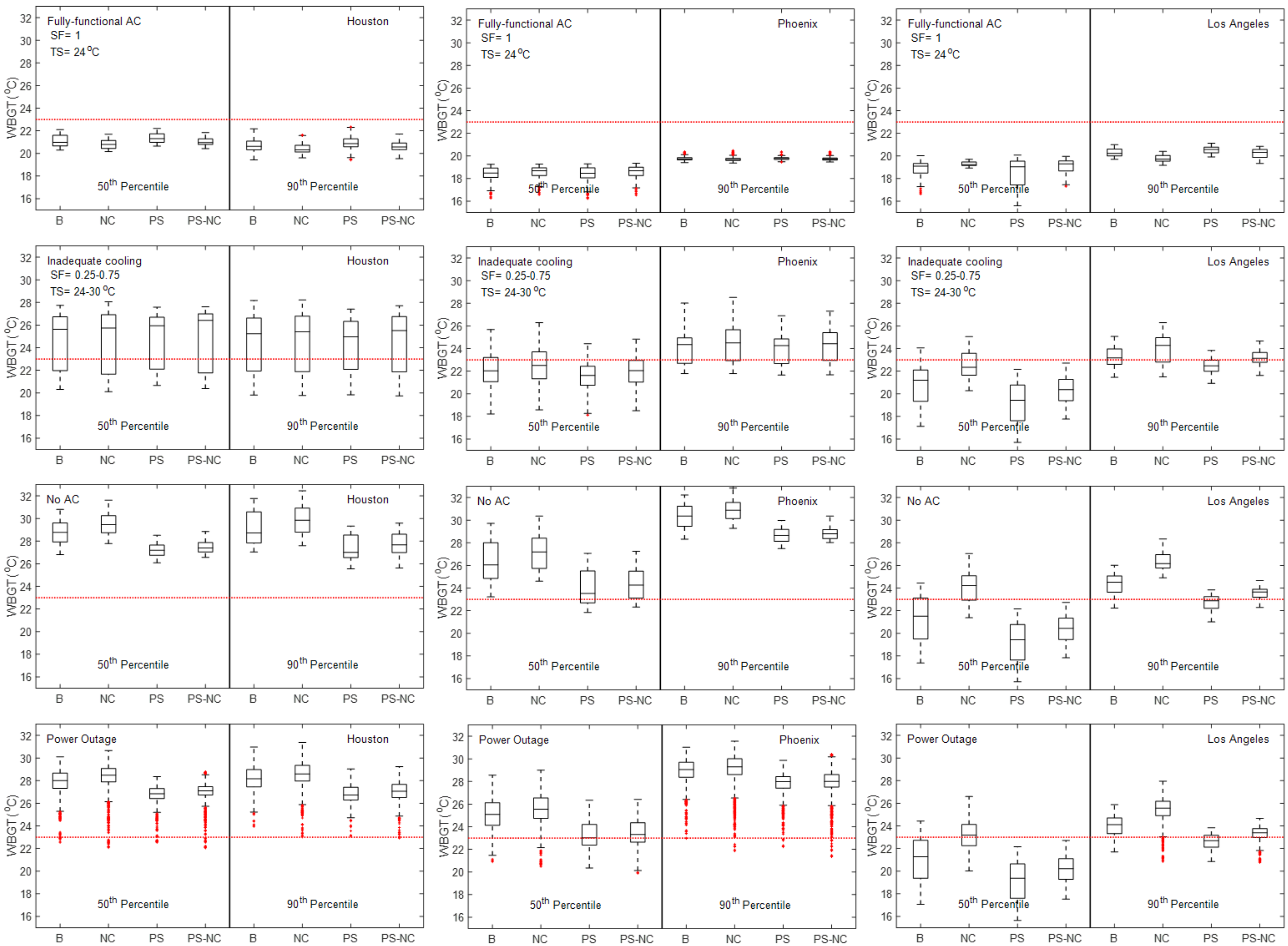


Figure 25. WBGT associated with four subsets of buildings (see parameter tree in figure 24) at days with 50th and 90th percentiles of outdoor daily mean dry-bulb temperature.

Based on this data, it can be inferred that building characteristics play a trivial role in thermal comfort when AC is fully functional (the top row of plots). The same can be observed under inadequate cooling in Houston and Phoenix. In contrast, in Los Angeles, indoor thermal conditions show considerable sensitivity to building characteristics even under inadequate cooling (In Phoenix and Houston it becomes significant only under No AC or power outage scenario). Notably, at both percentiles, overheating is more sever in buildings compliant to the newer energy codes. Under "No AC" and "power outage" cases (as well as "inadequate cooling" scenario in Los Angeles), the difference in exposure is large enough to cause statistically significant health impacts based on data presented in Section 2-2-2. This is a previously observed phenomenon in the literature for energy codes in Australia and UK[28], an is in-line with findings in (Ren, Wang, and Chen 2014; Mulville and Stravoravdis 2016; McLeod, Hopfe, and Kwan 2013; Taylor et al. 2018). From a physical standpoint, the excess overheating is due to more stringent insulation requirements and air-tightness in new codes, which impedes buildings ability to lose heat during the night. This can potentially have significant complications, especially because buildings are responsible for a large portion total energy use in US and worldwide, and any viable path towards reducing dependency of fossil fuels involves more stringent building energy codes. In addition,

[28] Author's own published work explores this phenomenon in US climates under the power outage scenario. See:
(Baniassadi, Heusinger, and Sailor 2018)
(Baniassadi et al. 2018)
(David J Sailor et al. 2019)

there is a consensus on the role of anthropogenic emissions in climate change, which can then lead to more intense and frequent heat events, highlighting the possibility of a positive feedback loop. On the one hand, more stringent building codes are needed to reduce emissions. On the other hand, as an unintended consequence of stringent codes, indoor overheating can lead to a higher market penetration of AC. Considering author's extensive review of literature on codes in different climates and exploration of U.S. building codes and climates (see (Baniassadi et al. 2018; David J Sailor et al. 2019; Baniassadi and Sailor 2018; Baniassadi, Heusinger, and Sailor 2018)), as well as the result presented here, it is not possible (and more importantly, not helpful) to generalize the impact of energy codes on overheating inside buildings. It is a phenomenon that is highly dependent on the baseline code, building type, underlying climate, occupant behavior, the used heat threshold, and the time and day of interest. For example, as the author reported in (Baniassadi, Heusinger, and Sailor 2018), for units on the top-floor of multi-family units in Phoenix, and under the hottest day in the TMY3 data, overheating inside buildings compliant to IECC2012 is less intense than that of IECC2006 (which is in contrast to what is presented here[29]), whereas in Albuquerque, NM, the opposite was observed. Regardless of these discrepancies caused by the different contexts, the existing evidence converges on the **potential** of overheating as an unintended consequence of energy efficiency under some scenarios, which should be enough to drive policy change.

[29] A possible explanation is the rooftop albedo, which is not governed by code in single family units.

Another important observation is the mitigation potential from the non-mandated strategies. As these results (Figure 25) suggest, a combination of rooftop albedo, operable windows, and shade on exterior walls can considerable mitigate indoor WBGT at both days in all three cities. Notably, none of these factors are currently regulated by codes (for single family residential units). When coupled with the new code, as seen in the NC + PS scenario, these strategies can compensate for the unintended consequence of the stringent energy code. However, it should be noted that in extreme cases (NO AC and power outage at 90th percentile in Houston and Phoenix) indoor conditions inside buildings remains extremely uncomfortable even with the mitigation from these interventions, highlighting an inherent limit to passive survivability of typical[30] buildings in these climates.

[30] Note the word "typical". Author acknowledges the technological and design advances that can result in comfortable conditions in high-end passive buildings. However, at the moment, that only applies to a very small number of buildings, with no evidence suggesting that it will become standard practice in the single-family home construction industry.

4. CONCLUSIONS, LIMITATIONS, AND RECOMMENDATIONS FOR FUTURE RESEARCH

4.1. Summary of findings and discussions

This section summarizes the findings of this dissertation as they relate to research objectives introduced in Section 1-4-1.

Objective 1: Estimate citywide indoor heat exposure in Houston, TX (for integration into a health-outcomes model)

Simulations (as described in Section 2-2) resulted in a spatial and temporal distribution of indoor exposure to heat among the elderly Houstonians at census block groups. It was confirmed that AC prevalence is the key explanatory variable regarding the spatial distribution. A relatively weaker association was found between indoor exposure and common socio-economic variables such as income or racial composition of neighborhoods. Finally, it was found that on average, indoor conditions are disassociated with outdoor temperatures, which can be explained by the high AC prevalence in the city.

With respect to the end impacts, it was found out that integrating time-series of estimated indoor heat exposure into and epidemiological model improves its performance beyond models that use outdoor temperature as a surrogate or use census block group AC prevalence as a static number. Olenick's findings (R. O'Lenick et al. 2019) based on this data implicated indoor exposure to heat in certain health outcomes. In specific, ORs between circulatory and heat-related mortality and maximum indoor WBGT were statistically significant.

Objective 2: Quantify exposure to indoor heat in climates with high AC prevalence

From the measurement campaign described in Section 2.1, it was found that more than a third of elderly Houstonians are over-exposed to indoor heat based on CIBSE's time threshold during a typical summer. In almost all cases, this was caused by malfunction or inappropriate use of AC, which was associated to economic issues or physiological ability to adapt. In addition, it was found that during a city-wide disaster that results in a large-scale power outage (hurricane Harvey), the ability of this population group to adapt to heat is very limited. Therefore, under such scenarios, passive survivability of buildings is the only protective factor against heat. Hence, as the next step, the author used thermal simulation of buildings to assess indoor overheating in a variety of AC availability scenarios in three cities. Simulation showed that passive survivability of an average building in Phoenix and Houston is very poor, even under typical summers. However, based on the survey data that was coupled to the simulations, the number of citizens (65 and older) who do not have any type of AC in Houston and Phoenix is very small. Nevertheless, it was found out that a semi-functional AC (due to high thermostat setpoint or system faults) can also potentially expose residents of Houston and Phoenix to health-implicating levels of heat, and that it implicates a considerable population size across the three cities. Finally, the highest risk was identified in the case of large-scale power outages (especially in Phoenix and Houston), that can increase the population size exposed to potentially dangerous levels of heat by up to 162 times the baseline value (number of people who don't have AC).

Objective 3: Identify potential compounding factors and mitigation strategies

By comparing indoor thermal conditions at two different days, the sensitivity of indoor conditions to outdoor signals was analyzed. On average, it was found that indoor WBGT increases between 0.6 and 0.8 ˚C per 1 ˚C increase in outdoor air temperature in buildings with inadequate AC (the most important group based on population size). Hence, considering the consensus in projections of more frequent and more intense heat waves in all three cities, it can be expected that under business as usual scenario (both in terms of climate, urban development, and building construction practices), average level of heat that an elderly person is exposed to will become more intense in near to mid-future scenarios.

Regarding the building characteristics, the most important observation was that with current trends in energy codes and construction practices, passive survivability of typical residential buildings is not improving. Notably, it was found that a few relatively low-cost strategies (none of which are currently mandated by codes) can significantly mitigate indoor overheating. However, in Phoenix and Houston, without AC, almost all buildings frequently overheat (with respect to the threshold that represents the elderly) even with the mitigation strategies. This highlights the fact that during large-scale power outages coincident with heat events in Phoenix and Houston, interventions on the building-side (at least those that are financially feasible in typical residential buildings) are not enough to protect elderly occupants from heat.

4.2. Policy recommendations

The author has several policy recommendations based on the findings of this study. First and foremost, resiliency to heat and passive survivability of buildings should be incorporated in building energy codes. Similar to the way that building energy codes are enforced, a "prescriptive pathway" (which will most likely be used in single-family residential buildings) could mandate the use of climate-specific solutions for passive survivability. These requirements need to be developed for each climate. A "performance" pathway (most likely to be used in multi-family units) can provide flexibility in design by regulating the passive survivability directly. For example, buildings may be required to be able to maintain safe thermal environments for power outages of a certain duration (based on historic power outage data) at a certain percentile of outdoor temperature. Similar to energy, this compliance could be assessed using whole-building energy simulations. In addition, the author encourages revitalizing the use of thermal mass in the form of phase change material (a transition to traditional mass materials is unlikely because of costs) in conjunction with the concept of time factor, which is the time it takes for the building to reach a predefined threshold. In the prescriptive pathway, pre-calculated tables could provide designers, contractors, and auditors with the amount of PCM needed per m^2 of the living area based on climate and envelope properties. In the performance pathway, the time factor itself could be mandated while allowing designers to come up with the most effective suite of strategies (including thermal mass) to meet the design criterion.

The second recommendation is regarding the energy poverty component and economic hardship that causes residents of low socio-economic status to rely on dysfunctional AC units. Many US cities (including the three cities discussed in this dissertation) have support programs to help low-income families with their utility bills. These programs could be improved upon by inclusion of support for preventative maintenance and repair of broken AC systems. In addition, based on the finding in chapter two, it is important for such programs to be proactive, to make sure socially isolated elderly (especially those with low-income) also benefit from the program.

The third policy recommendation is regarding the case of summertime power outages. Although there are many reasons (unrelated to concerns of this study) for promoting decentralized electricity infrastructure, the author's findings provide yet another incentive for pursuing reliable and resilient power infrastructure. In addition, similar to Section 2-2, predictive data for passive performance of buildings under summertime power outages at the neighborhood scale must inform emergency responses. In other words, the average passive performance of buildings at the neighborhood scale should be included in the process of determining the priority of neighborhoods to allocate resources in response to large-scale summertime power outages[31]. Currently, such data is not available for any US city. The large set of data (EnergyPlus outputs) generated for this dissertation could be used to associate certain building characteristics (those that are

[31] Currently, instead of building performance, its common socio-economic correlates (such as income) are included in such programs.

included in the parameter tree) to indoor overheating potential for the three studied cities. Therefore, author is making these data (alongside with necessary post-processing scripts) publicly available. The main benefit of such datasets (and correlations that associate building characteristics to indoor overheating potential) is that they could be used by public health officials and policy makers who might not have the background to perform building performance analysis. As a result, if data for certain characteristics of the building stock is available at spatial resolution of interest, (comparative) estimates of indoor thermal conditions in an average building (such Figure 13 in Chapter 2) can be obtained without running hourly simulations. This can then be used to identify most vulnerable neighborhoods based on building characteristics that determine average indoor heat exposure threat.

The author's final recommendation is to improve passive survivability of buildings by increasing awareness on the potential threat of large-scale power outages. This needs to be done both for the general public (to increase the demand for high-performance buildings) as well as those involved in the construction industry. Education and increasing awareness are important because passive survivability can only be achieved by disrupting the status quo of the construction industry which is highly dependent on AC. Since this might increase the initial costs[32], studies like this can be

[32] Although, arguably, there is a payback since passive design strategies reduce cooling energy demand.

used to inform the public of the threat of summertime power outages and justify the push for resilient buildings.

4.3. Limitations

4.3.1. Indoor heat thresholds

As mentioned in Section 2-1-1-2, research and data availability on thresholds for health-implicating indoor heat is very limited. Notably, part of the result presented in this document is sensitive to the selected threshold which was chosen based on author's analysis of the limited available data. More importantly, impacts of heat on the human body cannot simply be predicted by exposure to WBGT above a certain threshold. Duration of exposure, and its intensity (degrees above the threshold) are also determining factors. However, currently, the required data are not available.

With respect to intensity, there are several dose-response curves such as Figure 26 (from (Garzón-Villalba et al. 2017)). However, all of these data were gathered from young healthy individuals, mostly while exerting physical force. Hence, are not applicable for elderly in residential settings.

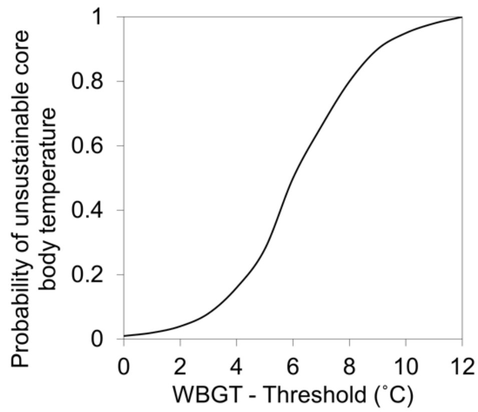


Figure 26. Dose-response of probability of unsustainable core body temperature (vertical axis) as a function of the difference between WBGT and the associated threshold (horizontal axis). Figure rendered based on data from (Garzón-Villalba et al. 2017).

Assuming the same curve is applicable for the elderly will provide additional insights on the actual end-impacts of exposure. For example, as Figure 27 shows, the exposure axis in all figures of in Chapter 3 can be converted to probability of unsustainable core body temperature.

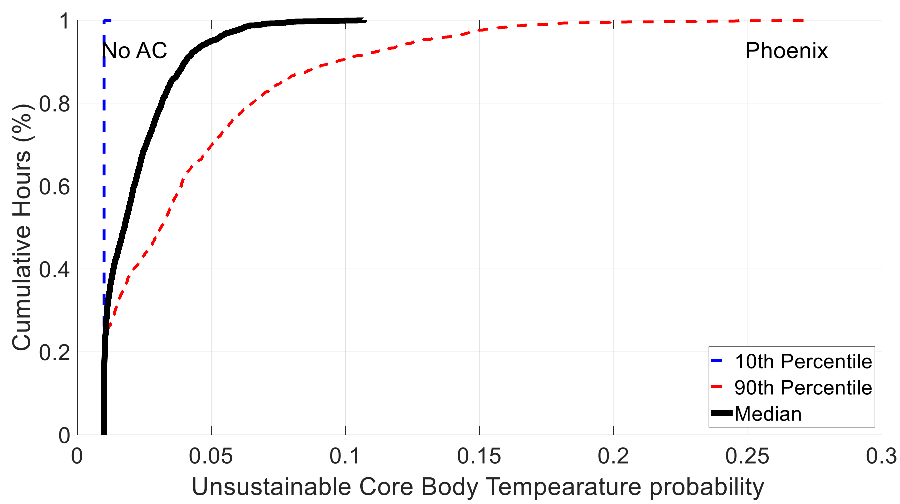


Figure 27. Cumulative distribution of hours and probability of unsustainable core body temperature. This figure is the same as those presented in chapter three with the exception that the horizontal axis is showing a health outcome (risk) instead of WBGT (exposure)

If this type of data was available, assessing the problem of indoor overheating and its possible solutions could be significantly more focused on actual health outcomes. Different building characteristics and AC functionality scenarios affect different parts of the exposure curve. For example, as this author explored in (Baniassadi et al. 2019), when the most extreme cases are considered, the impact from building energy codes in general can be more positive. As another example, author's assessments of benefits of using thermal mass (in the form of Phase Change Materials) in buildings showed that its mitigation potential is highly dependent on temperature range of the heat event, as well as the material melt temperature (Baniassadi, Sailor, and Bryan 2019). Therefore, having insight on the end-impacts (health outcomes) instead of exposure alone can be helpful in developing targeted solutions. This was in part addressed in this dissertation (Section 2-2-

2). However, we are currently far from having reliable dose-response curves of indoor exposure to heat in elderly.

4.3.2. Weather data

The author faced three limitations with respect to the available weather data.

4.3.2.1. Spatial variations

Variations in ambient temperature across different part of a city can be significant. Distant from the shore, vegetation cover, effective albedo, morphology, level of anthropogenic heat, and many different factors may result in distinct micro-climates within an urban area. However, reliable data (that includes **all** weather variables required by EnergyPlus) are only available at coarse scales, mostly from airport locations that are far apart. Hence the author could not account for these variations.

4.3.2.2. Extreme heat event profiles

The inherent limitation of using TMY3 data is the exclusion of extreme events. One method to obtain such data for EnergyPlus simulations is to merge data from different sources (all required variables cannot be obtain from a single data stream) to generate weather files for extreme events. In such cases, there will be fundamental inconsistencies[33] in the way that weather files are generated. In addition, from a

[33] With help from Dr. Jannik Huesinger (current affiliation: Technical University of Braunschweig), author generated such data for Phoenix from different data sources (NREL V1, Mesowest V1, NREL MTS, NREL PSM, Mesowest V2) and observed significant variations.

probability standpoint, extreme cases are less informative than heat events in typical summers. Hence, they are excluded from this study.

4.3.2.3. Future scenarios

An important consideration in studies similar to this dissertation is the impacts from a changing climate. In theory, this can be easily analyzed by simulating the same set of buildings using weather files generated from future projections. A common approach in the building science literature is the use of morphing technique in which data from global circulation models (GCM) is morphed into hourly data based on current patterns. However, the key limitation of this approach is the neglection of local climates and urban morphology that are not reflected in GCM's. A more sophisticated approach is to couple regional climate models (such as WRF) with GCM's to include the impacts from local signals. In fact, the author already made an effort on this front (Baniassadi et al. 2019). However, these sophisticated models also require a large number of assumptions with respect to different parameters. A possible solution is to test different models and assumption to provide a range of outcomes. However, that was beyond the scope of this dissertation. As a workaround, to refrain from subjectively selecting one model over another, the scope was limited to presenting the sensitivity of indoor thermal conditions to outdoor temperatures, which provides an opportunity to assess the outcomes of different projections.

4.3.3. Building Stock Characteristics

As demonstrated by the data presented in Figure 20, indoor thermal conditions (especially in Phoenix and Los Angeles) are highly dependent on the sizing factor (SF) and thermostat setpoint (TS). While the author estimated the population size that fall into a range of SF and TS values labeled as inadequate cooling, there is no data on the distribution within this group. Hence, it was not possible to provide a more detailed estimate of exposure and population size.

Finally, as mentioned in the methodology, the sample used in Chapter 3 did not include pre-1970's building with concrete blocks as the main construction material. If reliable data for the fraction of buildings with thermally massive walls were available, our sample would have been a better representative of the existing building stock. However, as previously mentioned, the majority of new constructions are wood-frame. Therefore, the average building in these cities is becoming more similar to what was presented in this dissertation.

4.4. Suggested areas for future research

Based on the main limitations of this study, a few areas for future research are suggested:

Since our current knowledge about exposure and its associated health-outcomes is very limited, future research should focus on generating empirical correlations that predict certain health outcomes as a function of exposure for residents under free living conditions. The focus should be on the elderly in their normal living condition. One outcome of such efforts will be reliable thresholds that can be used as upper limits in building energy codes, or other mandated regulations about passive survivability of buildings.

Through well-designed measurement campaigns and surveys, a dataset on the sizing factor (SF) and thermostat setpoint (TS) among the elderly populations in urban areas of interest should be generated. This will help narrowing down the problem of "inadequate cooling" based on reliable estimates of the distribution of SF and TS in each city, and better allocate resources in support programs. In addition, the author hypotheses that both variables are a function of income. Testing this hypothesis and developing correlations that can estimate SF and TS based on income can be very helpful for future research and policy implementation efforts.

Generating future data for assessing building energy performance under climate change is an active area of research. This work serves as another incentive for this drive, while also highlighting the need to focus on generating hourly data for future heatwaves. In addition, a meta-study is needed to assess current approaches for urban areas and provide a standard framework to be used in efforts similar to this dissertation.

To help develop policies suggested in Section 4-2, research should help develop an estimate of passive performance during power outages at neighborhood scale to be used in prioritizing resources during emergencies. Moreover, climate-specific solutions need to be assessed through a consistent framework to help develop the suggested "prescriptive path" for passive survivability compliance in energy codes.

4.5. Resulting publications

The following is the list of published (and under review) papers and conference presentations that resulted (entirely or in part) from this work:

Journal papers:

[1] A. Baniassadi, D.J. Sailor. 2018. Synergies and trade-offs between energy efficiency and resiliency to extreme heat - a case study. *Building and Environment* **(related to chapter 3)**

In this study, the passive survivability of archetype residential buildings during power failure scenarios that coincide with extreme heat conditions in Houston, TX and Phoenix, AZ was modeled. Results suggested that in older constructions, the indoor thermal conditions will easily reach dangerous levels during such episodes. In both cities, the discomfort index reaches the critical threshold in less than 6 h after the power outage. In addition, our analysis highlighted the importance of the definition of thermal resiliency metrics in interpreting the results of the simulations.

[2] A. Baniassadi, J. Heusinger, D.J. Sailor. 2018. Energy efficiency vs resiliency to extreme heat and power outages: The role of evolving building energy codes. *Building and Environment* **(related to chapter 3)**

In this study, we investigated the performance of high-rise residential apartment buildings under a three-day power outage scenario coinciding with a three-day heat wave and investigated the effect of building code on resiliency to heat. We observed a synergy between energy efficiency and resiliency to heat in warmer climates. However, in heating-dominated climates, newer codes can potentially have an adverse effect on heat resiliency of buildings.

[3] A. Baniassadi, D.J. Sailor, P.J. Crank. G.A. Ban-Weiss. 2018, Direct and indirect effects of high-albedo roofs on energy consumption and thermal comfort of residential buildings. *Energy and Buildings* **(related to chapter 3)**

Energy saving and thermal comfort benefits of high albedo roofs have two components: 1- Direct benefits to individual buildings by reducing absorbed shortwave radiation through the roof, and 2- Neighborhood-scale indirect benefit resulting from reduced ambient air temperatures, particularly when high-albedo surfaces are deployed on a large scale. This study is was effort to quantify the relative importance of these direct and indirect benefits and identify how they are affected by building and climate characteristics. We used whole-building energy simulations of a set of archetypical single-family residential buildings in three locations with distinct characteristics within the Los Angeles area (one coastal, and two inland). Our simulations showed that benefits from the indirect effect can be the same order of magnitude as the direct effects. More importantly, these benefits depend on the climate and building characteristics.

[4] A. Baniassadi, D.J. Sailor, E. S. Krayenhoff, A. M. Broadbent, M. Georgescu. Passive survivability of buildings under a changing urban climate. *Environmental Research Letters* **(related to chapter 3)**

In this paper, we compared indoor air temperature inside archetypical single-family residential buildings without AC at the start and middle of the century in eight U.S. cities. Our analysis showed that summertime overheat time may increase by up to 25% by the middle of century. Moreover, we find that, while newer building energy codes reduce thermal comfort under moderate outdoor weather, they perform better under extreme heat.

[5] A. Baniassadi, D.J. Sailor, H. Bryan. 2018. Effectiveness of phase change materials in improving the resiliency of residential buildings to extreme thermal conditions. *Solar Energy* **(related to chapter 3)**

In this paper, we studied the effectiveness of PCMs in improving the resiliency of buildings during extreme events. The results suggest a considerable dependence on the timing and duration of power/air conditioning loss episode, the melt temperature of the material, and the underlying climate. We found out that under some conditions it is possible to optimize melt temperature for both energy efficiency and heat resiliency, while under other conditions, optimizing for one outcome adversely affects the other.

[6] D. J. Sailor, A. Baniassadi, C. R. O'Lenick, O. V. Wilhelmi. 2018. The Growing Threat of Heat Disasters. *Environmental Research Letters* **(related to chapter 3)**

In this study we looked at the case of heat disasters (large-scale summertime power outages) in 20 US cities. Using simulations, we found that residential buildings in many US cities are highly vulnerable to heat disasters—with more than 50 million citizens living in cities at significant risk. This situation will be exacerbated by intensification of urban heat islands, climate change, and evolving construction practices. It is therefore crucial that future building codes consider thermal resiliency in addition to energy efficiency.

[7] C. R. O'Lenick, A. Baniassadi, R. Michael, J. Boehnert, X. Yu, O. V. Wilhelmi, M. H. Hayden, C. Wiedinmyer, A. Monaghan, P. J. Crank, J. Heusinger, K. Zhang, D. J. Sailor. A case-crossover analysis of the short-term effect of indoor thermal comfort on mortality and hospitalizations among the elderly in Houston, Texas. Under review in *Environmental Health Perspectives* **(related to chapter 2)**

We evaluated the role of indoor heat exposure on heat-related mortality and morbidity among the elderly (≥ 65 years) in Houston, Texas. Positive, significant odds ratios (OR) were observed between circulatory and heat-related mortality and maximum indoor Discomfort Index (a combined measure of temperature and humidity), suggesting a considerable increase in the odds of death due to exposure to high indoor heat. For circulatory deaths, associations were strongest when indoor heat exposure was defined using minimum indoor temperature, suggesting that high nighttime temperatures may play a prominent role in disease processes that lead specifically to circulatory related deaths.

[8] C. R. O'Lenick, O. V. Wilhelmi, R. Michael, M. H. Hayden, A. Baniassadi, C. Wiedinmyer, A. J. Monaghan, P. J. Crank, D. J. Sailor. 2019. Urban heat and air pollution: A framework for integrating population vulnerability and indoor exposure in health risk analyses. *Science of the Total Environment* **(related to chapter 2)**

In this paper, we explored the linkages between vulnerability science frameworks and epidemiological conceptualizations of risk to propose a novel conceptual framework through which estimates of indoor conditions, household-level vulnerability data, and spatially resolved ambient air pollution and meteorological data can be leveraged to characterize current and future health risks to air pollution and extreme heat, indoors and outdoors. We also described an approach for estimating household-level and neighborhood-level indoor air quality and heat exposure in U.S. cities.

[9] A. Baniassadi, D.J. Sailor, G.A. Ban-Weiss. 2019. Potential energy and climate benefits of super-cool materials as a rooftop strategy. *Urban Climate* **(side project related to chapter 3)**

This study was an effort to quantify the potential benefits of applying the newly developed "super cool" materials on building rooftops. Our results suggest that in all climates, the surface temperature of the super-cool rooftop remains below the ambient air temperature throughout the year, resulting in a negative average daily sensible heat flux. In addition, we found that the new technology can double the cooling energy saving compared to typical white roofs.

[10] A. Baniassadi, J. Heusinger, D.J. Sailor. 2018. Building Energy Savings Potential of a Hybrid Roofing System Involving High Albedo, Moisture Retaining Foam Materials. *Energy and Buildings* **(side project related to chapter 3)**

In this study, an innovative rooftop solution was proposed and evaluated using computer simulations. This proposed roof technology simultaneously incorporates the positive features of common high albedo and vegetated green roofs. The results show the proposed roof technology can outperform the other two technologies in all U.S representative climates. In addition, the preliminary economic assessment suggests this technology can be viable and may have advantages over competing strategies.

[11] K. E. Brown, A. Baniassadi, J. V. Pham, D. J. Sailor. 2019 Effects of rooftop photovoltaics on building cooling demand and sensible heat flux into the environment. Under review in *ASME Journal of Engineering for Sustainable Buildings and Cities* **(side project related to chapter 3)**

This study investigates potential negative impacts of rooftop PV on building energy demand and urban environment. Results indicate that the daily cooling energy penalty to due blockage of outgoing longwave radiation can be 4.9—11.2% of the PV generation depending on the configuration (compared to a white roof). In addition, we found out that rooftop PV can increase the daytime heat flux by more than a factor of 10.

[12] A. Baniassadi, D.J. Sailor, C.R. O'Lenick, P.J. Crank, T. A. Reddy, M.M. Chester, O.V. Wilhelmi. 2019. Indoor overheating in the age of mechanical air conditioning. (Under final preparations) **(related to chapter 3)**

This paper is a condensed version of chapter 3.

Conference Presentations:

[1] A. Baniassadi, D. J. Sailor, C. R. O'Lenick. Indoor air quality and thermal comfort for elderly residents in Houston TX—a case study. International Building Physics Conference (IBPC), Syracuse, NY, Sep 2018 (Oral)

Based on section 2.1.2.1 of this dissertation.

[2] O. Wilhelmi, C. O'Lenick, D. Sailor, R. Michael, M. Hayden, A. Baniassadi, A. Monaghan, C. Wiedinmyer, PJ. Crank, Extreme Heat and Ozone in Houston: Assessing and Reducing Health Risks. AGU fall meeting, Washington, D.C., Dec 2018 (Oral)

A condensed version of journal paper [8]

[3] A. Baniassadi, D.J. Sailor, P.J. Crank. G.A. Ban-Weiss. Direct and indirect effects of high-albedo roofs on energy consumption and thermal comfort of residential buildings. 10th International Conference on Urban Climate, New York, NY, Aug 2018 (Oral)

A condensed version of journal paper [3].

[4] D. J. Sailor, A. Baniassadi, Resiliency of Residential Buildings During Extreme Weather Events – Case Study of Power Outages During Hurricane Harvey in Houston, TX. 10th International Conference on Urban Climates (ICUC), New York, NY, Aug 2018 (Oral)

Based on section 2.1.2.2 of this dissertation.

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APPENDIX A

STEPS FOR REPRODUCING RESULTS IN SECTION 2.2

Weighted average estimates of indoor temperature and relative humidity at census block group can be reproduced using these steps:

A.1. IDF file for parametric runs

The first step is to run the IDF file ("model.idf") in the root folder of the data repository under the weather files for all climate zones for 16 years (2000-2016). This can be done using group simulation tab of EP-Launch. The folder structure needs to be the following:

Local address/zone_folder/year_folder/[34]

This will create 144 result files in each year folder and needs to be repeated for all five zones. The author is also providing the necessary weather files that he generated using the HRLSD simulation outputs. However, using them requires permission from Monaghan et al. (Monaghan et al. 2014).

A.2. Reading the output

Running these simulations will result in a large number of output CSV files (one file per simulation). The following Matlab code can read the data from CSV files and generate matrices that include the data from each archetype for all years. The code needs to be run 5 times (5 climate zones)

```
clear;
h = waitbar(0,'Please wait...');
```

[34] The year folder name format is 2XXX (e.g., 2004)

```
for i=1:144
   WBGTSF(1,i)=i;

end
for year= 1:17
   y=1999+year;
   initial=2+(year-1)*3672;
   for archetype=1:144
s1='C:\Users\abanias1\Google Drive\Research\EPA\EPA buildings\zone-5\';
       s2=num2str(y);
              if archetype<10
       s3='\00';
       elseif archetype<100
              s3='\0';
       else
       s3='\';
              end
       s4=num2str(archetype);
s5='.csv';
ss=[s1 s2 s3 s4 s5];
filename=char(ss);
delimiter = ',';
startRow = 2;
formatSpec = '%*s%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'EmptyValue'
,NaN,'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
fclose(fileID);
AirTemperatureHourly = dataArray{  :, 1};
AirRelativeHumidityHourly = dataArray{:, 2};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirTemperatureHourly;
RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirRelativeHumidityHourly;
TWSF(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype).*atan(0.151977.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+8.313659).^0.5)+atan(Temperature(initial:(initial+numel(AirTemperature
Hourly)-1),archetype)+RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype))-
atan(RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
1.676331)+(0.00391838.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)).^1.5).*atan(0.023101.*RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype))-4.686035;
```

```
WBGTSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)=
0.33*Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+0.67*TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
0.048*(log10(0.3))*(TempTemperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)-TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype));
    end
%     for i=initial:(initial+numel(AirTemperatureHourly)-1)
%     Temperature(i,1)=y;
%     end
     waitbar(year / 17)
end
csvwrite('5',WBGTSF);
close(h)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%zone4

clear;
h = waitbar(0,'Please wait...');
for i=1:144
    WBGTSF(1,i)=i;

end


for year= 1:17
    y=1999+year;
    initial=2+(year-1)*3672;
    for archetype=1:144
s1='C:\Users\abanias1\Google Drive\Research\EPA\EPA buildings\zone-4\';
        s2=num2str(y);
                if archetype<10
        s3='\00';
        elseif archetype<100
                    s3='\0';
        else
        s3='\';
                end
        s4=num2str(archetype);
s5='.csv';
ss=[s1 s2 s3 s4 s5];
filename=char(ss);
delimiter = ',';
startRow = 2;
formatSpec = '%*s%f%f%[^\n\r]';
fileID = fopen(filename,'r');
```

```
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'EmptyValue'
,NaN,'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
fclose(fileID);
AirTemperatureHourly = dataArray{:, 1};
AirRelativeHumidityHourly = dataArray{:, 2};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirTemperatureHourly;
RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirRelativeHumidityHourly;
TWSF(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype).*atan(0.151977.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+8.313659).^0.5)+atan(Temperature(initial:(initial+numel(AirTemperature
Hourly)-1),archetype)+RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype))-
atan(RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
1.676331)+(0.00391838.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)).^1.5).*atan(0.023101.*RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype))-4.686035;
WBGTSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)=
0.33*Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+0.67*TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
0.048*(log10(0.3))*(TempTemperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)-TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype));
   end
%     for i=initial:(initial+numel(AirTemperatureHourly)-1)
%     Temperature(i,1)=y;
%     end
    waitbar(year / 17)
end
csvwrite('4',WBGTSF);
close(h)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%zone3

clear;
h = waitbar(0,'Please wait...');
for i=1:144
   WBGTSF(1,i)=i;

end

for year= 1:17
   y=1999+year;
```

```
   initial=2+(year-1)*3672;
   for archetype=1:144
s1='C:\Users\abanias1\Google Drive\Research\EPA\EPA buildings\zone-3\';
      s2=num2str(y);
            if archetype<10
      s3='\00';
      elseif archetype<100
               s3='\0';
      else
      s3='\';
            end
      s4=num2str(archetype);
s5='.csv';
ss=[s1 s2 s3 s4 s5];
filename=char(ss);
delimiter = ',';
startRow = 2;
formatSpec = '%*s%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'EmptyValue'
,NaN,'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
fclose(fileID);
AirTemperatureHourly = dataArray{:, 1};
AirRelativeHumidityHourly = dataArray{:, 2};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirTemperatureHourly;
RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirRelativeHumidityHourly;
TWSF(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype).*atan(0.151977.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+8.313659).^0.5)+atan(Temperature(initial:(initial+numel(AirTemperature
Hourly)-1),archetype)+RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype))-
atan(RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
1.676331)+(0.00391838.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)).^1.5).*atan(0.023101.*RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype))-4.686035;
WBGTSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)=
0.33*Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+0.67*TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
0.048*(log10(0.3))*(TempTemperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)-TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype));
   end
```

```
%     for i=initial:(initial+numel(AirTemperatureHourly)-1)
%     Temperature(i,1)=y;
%     end
    waitbar(year / 17)
end
csvwrite('3',WBGTSF);
close(h)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%zone2

clear;
h = waitbar(0,'Please wait...');
for i=1:144
   WBGTSF(1,i)=i;

end

for year= 1:17
   y=1999+year;
   initial=2+(year-1)*3672;
   for archetype=1:144
s1='C:\Users\abanias1\Google Drive\Research\EPA\EPA buildings\zone-2\';
      s2=num2str(y);
            if archetype<10
      s3='\00';
      elseif archetype<100
               s3='\0';
      else
      s3='\';
            end
      s4=num2str(archetype);
s5='.csv';
ss=[s1 s2 s3 s4 s5];
filename=char(ss);
delimiter = ',';
startRow = 2;
formatSpec = '%*s%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'EmptyValue'
,NaN,'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
fclose(fileID);
AirTemperatureHourly = dataArray{:, 1};
AirRelativeHumidityHourly = dataArray{:, 2};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
```

```
Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirTemperatureHourly;
RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirRelativeHumidityHourly;
TWSF(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype).*atan(0.151977.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+8.313659).^0.5)+atan(Temperature(initial:(initial+numel(AirTemperature
Hourly)-1),archetype)+RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype))-
atan(RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
1.676331)+(0.00391838.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)).^1.5).*atan(0.023101.*RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype))-4.686035;
WBGTSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)=
0.33*Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+0.67*TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
0.048*(log10(0.3))*(TempTemperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)-TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype));
   end
%     for i=initial:(initial+numel(AirTemperatureHourly)-1)
%     Temperature(i,1)=y;
%     end
    waitbar(year / 17)
end
csvwrite('2',WBGTSF);
close(h)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%zone1

clear;
h = waitbar(0,'Please wait...');
for i=1:144
   WBGTSF(1,i)=i;

end

for year= 1:17
   y=1999+year;
   initial=2+(year-1)*3672;
   for archetype=1:144
s1='C:\Users\abanias1\Google Drive\Research\EPA\EPA buildings\zone-1\';
      s2=num2str(y);
            if archetype<10
      s3='\00';
      elseif archetype<100
```

```
            s3='\0';
        else
        s3='\';
            end
        s4=num2str(archetype);
s5='.csv';
ss=[s1 s2 s3 s4 s5];
filename=char(ss);
delimiter = ',';
startRow = 2;
formatSpec = '%*s%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'EmptyValue'
,NaN,'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
fclose(fileID);
AirTemperatureHourly = dataArray{:, 1};
AirRelativeHumidityHourly = dataArray{:, 2};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirTemperatureHourly;
RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=AirRelativeHumidityHourly;
TWSF(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)=Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype).*atan(0.151977.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+8.313659).^0.5)+atan(Temperature(initial:(initial+numel(AirTemperature
Hourly)-1),archetype)+RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype))-
atan(RH(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
1.676331)+(0.00391838.*(RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)).^1.5).*atan(0.023101.*RH(initial:(initial+numel(AirTemperatureHourly)-
1),archetype))-4.686035;
WBGTSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)=
0.33*Temperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)+0.67*TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype)-
0.048*(log10(0.3))*(TempTemperature(initial:(initial+numel(AirTemperatureHourly)-
1),archetype)-TWSF(initial:(initial+numel(AirTemperatureHourly)-1),archetype));
   end
%    for i=initial:(initial+numel(AirTemperatureHourly)-1)
%    Temperature(i,1)=y;
%    end
    waitbar(year / 17)
end
csvwrite('1',WBGTSF);
close(h)
```

In the next step, WBGT values need to be weighted based on prevalence of archetypes in each census block group. This can be done using the following Matlab code. The files “completeHCAD.csv” and “HCAD data.xlsx” contain the curated tax assessor’s data and are available in the root file of the data repository.

```
clear;
tic
h = waitbar(0,'Overal Progress');
filename = ‘Local Address\completeHCAD.csv';
delimiter = ',';
formatSpec =
'%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%
f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f
%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%
f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f
%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'TextType', 'string',
'EmptyValue', NaN,  'ReturnOnError', false);
fclose(fileID);
completeHCAD = [dataArray{1:end-1}];
clearvars filename delimiter formatSpec fileID dataArray ans;

[~, ~, raw] = xlsread(‘Local Address \HCAD data.xlsx','HCAD data','BX2:BX1561');
climatezone = reshape([raw{:}],size(raw));
[~, ~, raw] = xlsread(' Local Address \HCAD data.xlsx','HCAD data','b2:c1561');
ACfraction = reshape([raw{:}],size(raw));%column1= without AC -----%column2=with
AC
clearvars raw;
for cbg=1:length(completeHCAD)%cbg=census block group
climate=climatezone(cbg);
filename = num2str(climate);
delimiter = ',';
startRow = 2;
formatSpec =
'%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%
f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f
%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%
```

```
f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f
%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'TextType', 'string',
'EmptyValue', NaN, 'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine',
'\r\n');
fclose(fileID);
tempdata = [dataArray{1:end-1}];
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
WBGT=zeros(length(tempdata),144);
for arch=1:144
for t=1:length(tempdata)
WBGT
(t,arch)=tempdata(t,arch)*completeHCAD(cbg,arch)/sum(completeHCAD(cbg,:));
sum WBGT (t,cbg)=sum(DI(t,:));
weighedDI(t,cbg)=20*(ACfraction(cbg,2)-
ACfraction(cbg,1))/ACfraction(cbg,2)+ACfraction(cbg,1)/ACfraction(cbg,2)*sumDI(t,cb
g);
end
end
waitbar(cbg / length(completeHCAD))
end
%weighedtempabs=(abs((weighed WBGT)-20)+weighed WBGT -20)*0.5;
close(h)
toc
```

The output is a CSV file that includes hourly data of average weighted indoor WBGT for each census block group. This was directly fed into the health-outcomes model detailed in (R. O’Lenick et al. 2019).

APPENDIX B

ASSOCIATING SF TO ACTUAL AC FAULTS

This Section is a summary of author’s literature review regarding the degradation in AC capacity (that was represented by SF in this dissertation) due to different system faults. The purpose of this summary was to provide context for interpreting the results of chapter 3 (the inadequate cooling scenario). Based on these findings, author posits that in buildings with Faulty systems, an SF range of 25 – 75% is a realistic estimate, with SF=50% being the most probable.

Chen and Braun (Chen and Braun 2000) listed the following faults as common issues with residential AC systems: Condenser fouling, Evaporator fouling, Liquid line restriction, compressor wear, refrigerant leakage, refrigerant overcharge, and non-condensable gas. Then, they simulated the impacts from these faults at different fault intensities (defined as 5 levels) on the cooling capacity of a 5-ton residential AC unit. Notably, refrigerant leaking (which was reported to be the most common fault (Proctor 2000) had the most impact and reduced the capacity by 40%. Existence of non-condensable gas and compressor wear could also reduce the capacity by around 30%. Impacts from other faults we generally less than 10 %. However, it should also be noted that these data are generated for single faults; whereas in reality, multiple faults can occur simultaneously (specially in older systems). Palani et al. (Palani, O'Neal, and Haberl 1992) repeated the same analysis on a 3 ton system. They considered reduction in evaporator air flow, blocked OD fan air flow, presence of non-condensable gases, refrigerant undercharge (and overcharge), and blockages in refrigerant lines. Cooling capacity reduction due to individual faults were reported to be between 2-62 %, depending on the fault and its intensity. The other example is the work of Kim et al. (M.

Kim et al. 2009) who investigated faults in 2.5 ton heat pump and considered compressor leakage, improper outdoor air flow rate, improper indoor air flow rate, refrigerant undercharge, (and overcharge), and presence of non-condensable gases. They report refrigerant charge and compressor/reversing valve leakage as the main two faults; with a potential to reduce cooling capacity by 10 – 25 %.

Aside from these lab studies, Stephens et al. (Stephens, Siegel, and Novoselac 2011) characterized a variety of operational characteristics in 17 existing residential and light-commercial AC systems in Austin, TX. They observed that for almost all systems, air-flow rates were outside the recommended range (suggesting poor ductwork). Their data suggest that most of these systems were operating at 25-75% of their rated capacity.

Since AC refrigerant undercharge is the most common fault in residential systems (Mehrabi and Yuill 2017), several studies in the literature exclusively consider this variable. Mehrabi and Yuill (Mehrabi and Yuill 2017) reviewed the associations between AC capacity and refrigerant charge level in 24 papers and developed generalized relationships to describe the fault effects. They conclude that in fixed orifice systems (the more common type in residential systems), the mean value of normalized cooling capacity at 40% AC undercharge was 0.54. They also noted a significant agreement among the findings of different studies (when normalized), which was surprising considering that these studies were conducted on systems with different refrigerants and included both split and packaged units. Siegel and Wray (Siegel 2002) conducted superheat tests in the "as found" conditions and repeated them after calibrating the refrigerant charge in four California homes (two with new systems and two with old systems). They found that all systems had deficient refrigerant charges (17 – 33 %) and that their cooling capacity improved 18 – 38% after the calibration. Remarkably, the newest system was the one with the highest improvement. Other examples of lab tests on the impact of refrigerant charge level on cooling capacity of typical residential systems include (W. Kim and Braun 2012; Cheung and Braun 2017; Yoo, Hong, and Kim 2017). At refrigerant charge levels ≈ 50%, these studies report normalized cooling capacity reductions as high as 40 – 70 %.

The other common fault in residential AC systems is reduced evaporator air flow (due to evaporator fouling, filter saturation, or poor ductwork). The survey done by Stephens et al. (Stephens, Siegel, and Novoselac 2011) found that more than 50% of residential and light commercial AC systems have insufficient evaporator air flow. With respect to impacts on cooling capacity, Yang et al. (L. Yang, Braun, and Groll 2007) reported that a fouled evaporator can easily reduce the cooling capacity of a 3 ton system by around 5%. Yin et al. (Yin and Sweeney 2014) derived normalized gross cooling capacity as a function of flow fraction for a 5 ton TXV unit. Based on their findings, cooling capacity reduces by around 4% per 10% reduction in evaporator air flow. Rodriguez et al. (Rodriguez et al. 1996) conducted the same investigation while comparing FXO TXV systems. They reported similar findings for TXV, but also noted that the FXO system is around two times more sensitive to evaporator air flow.

APPENDIX C

STEPS FOR REPRODUCING THE RESULTS IN CHAPTER 3

C.1. Running the simulations

The simulations presented in this chapter were done using JEPlus under TMY3 weather files for the three cities that can be downloaded from EnergyPlus website (author also provided a copy in the data repository). In total, six JEPlus files are needed (three cities, two scenarios per city. The "normal" scenario refers to uninterrupted availability of AC throughout the summer while the "PO" scenario refers to the power outage scenario. The latter is similar to the normal scenario with the exception of three 24-hour power outages incorporated into the input files.

C.2. Post-process steps

The associated IDF and RVI files are all uploaded into the data repository. Once the simulations are done and ReadVars program generates output CSV files, The following Matlab code can post-process the output and calculate the required metrics.

C.2.1. Initial post-process

This Matlab function reads the output in CSV files and generate matrices of temperature and relative humidity.

```
tic;
clear;
%Read file names
filename = 'filenames.txt';
readfilenames;
h = waitbar(0,'process');
%main loop
for i=1:numel(filenames)
  %Read CSV
```

```
    readCSV;
   %calculations
    Temp(:,i)=temperature(:,1);
    RH(:,i)=relativehumidty(:,1);
    AC(:,i)=energy(:,1);
     waitbar(i / numel(filenames))
    fclose('all');
    i
    close('all');
end
close(h)
```

Here, “readfilenames” refers to the following function. In addition, “filenames.txt” (that should exist in the same folder) contains a list of all simulation folders (i.e. the location of output CSV files) under that scenario.

```
formatSpec = '%s%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', '', 'WhiteSpace', '', 'TextType',
'string',  'ReturnOnError', false);
dataArray{1} = strtrim(dataArray{1});
fclose(fileID);
raw = repmat({''},length(dataArray{1}),length(dataArray)-1);
for col=1:length(dataArray)-1
    raw(1:length(dataArray{col}),col) = mat2cell(dataArray{col},
ones(length(dataArray{col}), 1));
end
numericData = NaN(size(dataArray{1},1),size(dataArray,2));
rawNumericColumns = {};
rawStringColumns = string(raw(:, 1));
filenames = raw;
clearvars filename formatSpec fileID dataArray ans raw col numericData
rawNumericColumns rawStringColumns;
```

Finally, readCSV refers to the following function:

```
f=filenames{i};
filename1=char(f);
filename2='\eplusout.csv';
filename=[filename1 filename2];
delimiter = ',';
startRow = 50;
formatSpec = '%*s%f%f%*s%*s%f%[^\n\r]';
fileID = fopen(filename,'r');
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'TextType', 'string',
'EmptyValue', NaN, 'HeaderLines' ,startRow-1, 'ReturnOnError', false, 'EndOfLine',
'\r\n');
fclose(fileID);
temperature = dataArray{:, 1};
relativehumidty = dataArray{:, 2};
energy = dataArray{:, 3};
clearvars filename delimiter startRow formatSpec fileID dataArray ans;
```

Once the process is complete, “Temp”, “RH”, and “AC” matrices need to be manually saved into a data directory at the local machine. The file name format should be “Temp - City”, “RH - City”, and “energy - city” for “Temp”, “RH”, and “AC” (all inside the data directory). For the power outage simulations, the file names should have an additional “- PO”.

C.2.2. Secondary post-process

In this step, temperature and relative humidity data are used to calculate WBGT, and the degree-hours of WBGT over the threshold of 23˚C. The following Matlab code performs this task. Here, “City” and “Operation” are user inputs. Operation can either by “normal” or “PO” (power outage).

```
tic;
clear;
threshold=23;
h = waitbar(0,'process');
%main loop
city=inputdlg('city????');
operation = inputdlg('operation????');
load_variables;
for i=1:size(Temp,2)

TW(:,i)=Temp(:,i).*atan(0.151977.*(RH(:,i)+8.313659).^0.5)+atan(Temp(:,i)+RH(:,i))-
atan(RH(:,i)-1.676331)+(0.00391838.*(RH(:,i)).^1.5).*atan(0.023101.*RH(:,i))-
4.686035;
    WBGT(:,i)= 0.67*TW(:,i)+ 0.33*Temp(:,i)-0.048*(log10(0.3))*(Temp(:,i)-TW(:,i));
    WBGTover(:,i)=((WBGT(:,i)-threshold)+abs(WBGT(:,i)-threshold))/2;
    waitbar(i / size(Temp,2))
end
close(h)
```

In this code, "load_variables" refers to the following function:

```
    if strcmp(operation,'normal')==1
        if strcmp(city,'Phoenix')==1
            load('Local Address\RH - PHX.mat');
            load('Local Address\Temp - PHX.mat');
            load('Local Address\energy - PHX.mat');
        end
        if strcmp(city,'Houston')==1
            load('Local Address\RH - Houston.mat');
            load('Local Address\Temp - Houston.mat');
            load('Local Address\energy - Houston.mat');
        end
        if strcmp(city,'Los Angeles')==1
            load('Local Address\RH - LA.mat');
            load('Local Address\Temp - LA.mat');
            load('Local Address\energy - LA.mat');
        end
    end

    if strcmp(operation,'PO')==1
        if strcmp(city,'Phoenix')==1
            load('Local Address\outage\RH - PHX - PO.mat');
```

```
        load('Local Address\outage\Temp - PHX - PO.mat');
        load('Local Address\outage\energy - PHX - PO.mat');
    end
    if strcmp(city,'Houston')==1
        load('Local Address\outage\RH - Houston - PO.mat');
        load('Local Address\outage\Temp - Houston - PO.mat');
        load('Local Address\outage\energy - Houston - PO.mat');
    end
    if strcmp(city,'Los Angeles')==1
        load('Local Address\outage\RH - LA - PO.mat');
        load('Local Address\outage\Temp - LA - PO.mat');
        load('Local Address\outage\energy - LA - PO.mat');
    end
end
else
if strcmp(operation,'normal')==1
    if strcmp(city,'Phoenix')==1
        load('Local Address\RH - PHX.mat');
        load('Local Address\Temp - PHX.mat');
        load('Local Address\energy - PHX.mat');
    end
    if strcmp(city,'Houston')==1
        load('Local Address\RH - Houston.mat');
        load('Local Address\Temp - Houston.mat');
        load('Local Address\energy - Houston.mat');
    end
    if strcmp(city,'Los Angeles')==1
        load('Local Address\RH - LA.mat');
        load('Local Address\Temp - LA.mat');
        load('Local Address\energy - LA.mat');
    end
end

if strcmp(operation,'PO')==1
    if strcmp(city,'Phoenix')==1
        load('Local Address\outage\RH - PHX - PO.mat');
        load('Local Address\outage\Temp - PHX - PO.mat');
        load('Local Address\outage\energy - PHX - PO.mat');
    end
    if strcmp(city,'Houston')==1
        load('Local Address\outage\RH - Houston - PO.mat');
        load('Local Address\outage\Temp - Houston - PO.mat');
        load('Local Address\outage\energy - Houston - PO.mat');
    end
```

```
    if strcmp(city,'Los Angeles')==1
      load('Local Address\outage\RH - LA - PO.mat');
      load('Local Address\outage\Temp - LA - PO.mat');
      load('Local Address\outage\energy - LA - PO.mat');
    end
  end
```

C.2.3. Data curation

The following Matlab code was used to generate the data necessary to create Figures 17 - 19:

```
exist SimJobIndex;
if ans==0
read_job_index_file_lab_PC;
end
min_WBGT_total=0;
max_WBGT_total=0;
avg_WBGT_total=0;
avg_AC_use_total=0;
low_percentile=10;
high_percentile=90;
filter_table_lab_PC;
columnnumber=1;
clear WBGT_exposure;
clear AC_use;
clear Temp_exposure;
clear RH_exposure;
clear WBGT_exposure_vector;
clear WBGT_over;
for i = 1:numel(jobnumber)
  if jobnumber (i)==1
WBGT_exposure(:,columnnumber)=WBGT(:,i);
AC_use(:,columnnumber)=AC(:,i);
WBGT_over(:,columnnumber)=WBGTover(:,i);
Temp_exposure(:,columnnumber)=Temp(:,i);
RH_exposure(:,columnnumber)=RH(:,i);
columnnumber=columnnumber+1;
  end
end
%%
```

```
for t=1:3672
   min_WBGT_exposure(t)=prctile(WBGT_exposure(t,:),low_percentile);
      max_WBGT_exposure(t)=prctile(WBGT_exposure(t,:),high_percentile);
      avg_WBGT_exposure(t)=mean(WBGT_exposure(t,:));
               min_Temp_exposure(t)=prctile(Temp_exposure(t,:),low_percentile);
      max_Temp_exposure(t)=prctile(Temp_exposure(t,:),high_percentile);
      avg_Temp_exposure(t)=mean(Temp_exposure(t,:));
                     min_RH_exposure(t)=prctile(RH_exposure(t,:),low_percentile);
      max_RH_exposure(t)=prctile(RH_exposure(t,:),high_percentile);
      avg_RH_exposure(t)=mean(RH_exposure(t,:));

end
for t=745:2952
       min_WBGT_total=min_WBGT_total+prctile((WBGT_over(t,:)),low_percentile);
       max_WBGT_total=max_WBGT_total+prctile((WBGT_over(t,:)),high_percentile);
      avg_WBGT_total=avg_WBGT_total+mean(WBGT_over(t,:));
      avg_AC_use_total=avg_AC_use_total+mean(AC_use(t,:));
end
```

Here, “read-job-index-file-lab-PC” refers to the following function that creates an index table for all simulations. To run this code, “SimJobIndex.csv” and “SimJobIndex - PO.csv” that are generated by JEPlus should be copied to the Local Address.

```
%% Initialize variables.
if strcmp(operation,'normal')
filename = 'Local Address\SimJobIndex.csv';
else
filename = 'Local Address\SimJobIndex - PO.csv';
end
   delimiter = ',';
startRow = 2;
%% Read columns of data as text:
formatSpec =
'%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s%s
%s%[^\n\r]';
%% Open the text file.
fileID = fopen(filename,'r');
```

```
%% Read columns of data according to the format.
dataArray = textscan(fileID, formatSpec, 'Delimiter', delimiter, 'HeaderLines' ,startRow-
1, 'ReturnOnError', false, 'EndOfLine', '\r\n');
%% Close the text file.
fclose(fileID);
%% Convert the contents of columns containing numeric text to numbers.
raw = repmat({''},length(dataArray{1}),length(dataArray)-1);
for col=1:length(dataArray)-1
    raw(1:length(dataArray{col}),col) = dataArray{col};
end
numericData = NaN(size(dataArray{1},1),size(dataArray,2));
for col=[1,2,6,7,8,9,10,11,12,13,14,15,16,24,27,28,29,30]
   % Converts text in the input cell array to numbers. Replaced non-numeric
   % text with NaN.
    rawData = dataArray{col};
    for row=1:size(rawData, 1);
       % Create a regular expression to detect and remove non-numeric prefixes and
       % suffixes.
        regexstr = '(?<prefix>.*?)(?<numbers>([-]*(\d+[\,]*)+[\.]{0,1}\d*[eEdD]{0,1}[-
+]*\d*[i]{0,1})|([-]*(\d+[\,]*)*[\.]{1,1}\d+[eEdD]{0,1}[-+]*\d*[i]{0,1}))(?<suffix>.*)';
        try
            result = regexp(rawData{row}, regexstr, 'names');
            numbers = result.numbers;

           % Detected commas in non-thousand locations.
            invalidThousandsSeparator = false;
            if any(numbers==',');
                thousandsRegExp = '^\d+?(\,\d{3})*\.{0,1}\d*$';
                if isempty(regexp(numbers, thousandsRegExp, 'once'));
                    numbers = NaN;
                    invalidThousandsSeparator = true;
                end
            end
           % Convert numeric text to numbers.
            if ~invalidThousandsSeparator;
                numbers = textscan(strrep(numbers, ',', ''), '%f');
                numericData(row, col) = numbers{1};
                raw{row, col} = numbers{1};
            end
        catch me
        end
    end
end
%% Split data into numeric and cell columns.
```

```
rawNumericColumns = raw(:, [1,2,6,7,8,9,10,11,12,13,14,15,16,24,27,28,29,30]);
rawCellColumns = raw(:, [3,4,5,17,18,19,20,21,22,23,25,26]);
%% Replace non-numeric cells with NaN
R = cellfun(@(x) ~isnumeric(x) && ~islogical(x),rawNumericColumns);% Find non-
numeric cells
rawNumericColumns(R) = {NaN};% Replace non-numeric cells
%% Create output variable
SimJobIndex = table;
SimJobIndex.VarName1 = cell2mat(rawNumericColumns(:, 1));
SimJobIndex.Job_ID = cell2mat(rawNumericColumns(:, 2));
SimJobIndex.WeatherFile = rawCellColumns(:, 1);
SimJobIndex.ModelFile = rawCellColumns(:, 2);
SimJobIndex.AC = rawCellColumns(:, 3);
SimJobIndex.SF = cell2mat(rawNumericColumns(:, 3));
SimJobIndex.cooling_SetP = cell2mat(rawNumericColumns(:, 4));
SimJobIndex.window_u = cell2mat(rawNumericColumns(:, 5));
SimJobIndex.shgc = cell2mat(rawNumericColumns(:, 6));
SimJobIndex.wallR = cell2mat(rawNumericColumns(:, 7));
SimJobIndex.ceilingR = cell2mat(rawNumericColumns(:, 8));
SimJobIndex.floorR = cell2mat(rawNumericColumns(:, 9));
SimJobIndex.ELA = cell2mat(rawNumericColumns(:, 10));
SimJobIndex.N_axis = cell2mat(rawNumericColumns(:, 11));
SimJobIndex.roofabsorbtivity = cell2mat(rawNumericColumns(:, 12));
SimJobIndex.peope_density = cell2mat(rawNumericColumns(:, 13));
SimJobIndex.windowoperationsch = rawCellColumns(:, 4);
SimJobIndex.wall_shade_S = rawCellColumns(:, 5);
SimJobIndex.wall_shade_N = rawCellColumns(:, 6);
SimJobIndex.wall_shade_W = rawCellColumns(:, 7);
SimJobIndex.wall_shade_E = rawCellColumns(:, 8);
SimJobIndex.ceilingconstruction = rawCellColumns(:, 9);
SimJobIndex.OutsideBoundary = rawCellColumns(:, 10);
SimJobIndex.Outsideobject = cell2mat(rawNumericColumns(:, 14));
SimJobIndex.roofsun = rawCellColumns(:, 11);
SimJobIndex.roofwind = rawCellColumns(:, 12);
SimJobIndex.lentgh = cell2mat(rawNumericColumns(:, 15));
SimJobIndex.width = cell2mat(rawNumericColumns(:, 16));
SimJobIndex.W_multiplierSN = cell2mat(rawNumericColumns(:, 17));
SimJobIndex.W_multiplierEW = cell2mat(rawNumericColumns(:, 18));
%% Clear temporary variables
clearvars filename delimiter startRow formatSpec fileID dataArray ans raw col
numericData rawData row regexstr result numbers invalidThousandsSeparator
thousandsRegExp me rawNumericColumns rawCellColumns R;
```

In addition, “filter_table_lab_PC” has a set of switches (in form of IF statements) that can be used to include or exclude certain variables of parameter tree and define the desired range. The exclusion is simply done by temporarily converting the associated code line to a comment. The following is the code for “filter-table-lab-PC”. It should be noted that this code needs to be edited prior to running the main code of this subsection.

```
for i = 1:size(Temp,2)
jobnumber(i)=0;
%if string(SimJobIndex.AC(i))=='outage_LA'
if string(SimJobIndex.AC(i))=='always_avail'
if SimJobIndex.SF(i) == 0.25 || SimJobIndex.SF(i) == 0.5 || SimJobIndex.SF(i) == 0.75
if SimJobIndex.cooling_SetP(i) == 24 || SimJobIndex.cooling_SetP(i) == 30
  if SimJobIndex.shgc(i)== 0.4%|| SimJobIndex.shgc(i)== 0.5%|| SimJobIndex.shgc(i) ==
0.6% || string(SimJobIndex.shgc(i) )== 0.25%IECC2018=0.25  IECC2003=0.4
%No_Code<<2003=0.5%No_Code=0.6
% if string(SimJobIndex.lentgh(i) )== 12
% if string(SimJobIndex.N_axis(i) )== 0
 if SimJobIndex.roofabsorbtivity(i) == 0.45
% if string(SimJobIndex.peope_density(i) )== 0.02
 if string(SimJobIndex.windowoperationsch(i) )== 'always_avail'
 if string(SimJobIndex.wall_shade_S(i) )== 'nosun'
 if string(SimJobIndex.wall_shade_W(i) )== 'nosun'
 if string(SimJobIndex.ceilingconstruction(i) )== 'Interior_Ceiling'%Interior_Ceiling or
Flat_Roof
 if SimJobIndex.W_multiplierSN(i)== 3.6 || SimJobIndex.W_multiplierSN(i)== 5
%%%% couples (1|1  3.6|5  7.2|9)
jobnumber(i)=1;
% end
% end
% end
end
end
 end
 end
 end
 end
 end
 end
end
```

```
end
end
```

C.2.4. creating plots

With the main codes explained, the functions “plot_figures_cdf”, “dailyplots”, and “dailyplots” (all provided in the data repository) can be used to generate graphs for each scenario/city of interest. The function “start_hours” (also included in the repository) sets all the necessary indexes based on the actual date of 50th and 90th percentiles of outdoor dry-bulb temperature in each city.

C.2.5. calculating WBGT

The following equation was used to calculate indoor WBGT in this dissertation (Holmes et al., 2016):

$$WBGT = 0.67\ T_{pwb} + T_a - 0.048\log_{10}{}^{V}\ (T_a - T_{pwb}) \qquad \text{eq.1}$$

where T_{pwb} is psychrometric wet-bulb temperature (see eq.1), T_a is dry-bulb temperature, and V is air speed (assumed to be 0.3 m/s). Using this equation, the author assumed that inside residential buildings, radiant temperature is equal to air temperature. This assumption has been previously validated by the author in (Baniassadi and Sailor, 2018). Psychrometric wet-bulb temperature is calculated using the following equation:

$$T_{pwb} = T_a\ \mathrm{atan}\ [\ 0.151977\ (RH + 8.313659)^{1/2}] + \mathrm{atan}\ (T_a + RH\%) - \mathrm{atan}\ (RH\% - 1.676331) + 0.00391838\ (RH\%)^{3/2}\ \mathrm{atan}\ (0.023101 RH\%) - 4.686035 \qquad \text{eq.2}$$

where RH% is the relative humidity percentage.