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Heat, Wildfire and Energy Demand: An Examination of Residential Buildings and Community Equity

Chrissi Argyro Antonopoulos
Portland State University

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by

Chrissi Argyro Antonopoulos

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Dissertation Committee:
Vivek Shandas, Chair
Elliott Gall
Loren Lutzenhiser
Hal Nelson

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Abstract

Extreme heat and wildfire events are becoming more prolific and exacerbated by climate change, carrying significant implications for environmental and social systems. Residential buildings play a central role in protecting people from heat and pollutant exposure during extreme weather events, but the level of protection varies dramatically depending on building energy efficiency and technology availability. Low-income and communities of color have higher energy burdens compared to affluent populations, and underserved communities often do not have financial resources for, or access to, advanced building technologies. This dissertation explores the impacts of extreme heat and wildfire on residential buildings, focused specifically on occupant exposure risks related to energy performance and indoor air quality (IAQ). The research presented explores the complex influences that location and socio-demographics play on residential energy burdens, with a particular focus on how low-income households are impacted by inequitable energy systems.

This dissertation presents three essays that cover related aspects of IAQ, energy efficiency and equity. The first essay employs a dataset of over 16,000 homes to investigate the relationship between urban heat and residential building energy use, with a particular focus on access to air conditioning and the influence of building characteristics. The second essay presents an experimental assessment of interventions to reduce fine particulate matter ($PM_{2.5}$) in a home during a wildfire event, using data gathered during a large wildfire in Portland, Oregon in September 2020. The third essay uses data from a low-income energy efficiency program to explore how building

characteristics impact energy burdens in low-income housing. Collective findings from the research highlights the need for an energy efficient, resilient housing stock, and supports policies to advance energy equity as a top priority for decarbonizing the building sector.

Acknowledgements

No one person is an island, and I am extremely fortunate to have had the guidance and support of many incredible people throughout this journey. I would like to thank Dr. Vivek Shandas for being a stellar advisor and Chair, for always providing insightful feedback and suggestions, and for all the inspiring conversations about the impacts of heat on urban systems. To Dr. Loren Lutzenhiser, who was my original mentor and Chair during my Master's studies, and who inspired me to think about the role of people, behavior, and equity in residential buildings. To Dr. Elliott Gall who was willing to work with a non-engineer interested in IAQ, and who provided countless rounds of comments on methods, approaches, and presentation of findings, I am truly grateful. To Dr. Nelson who always brought the conversation back to policy and the importance of communicating research results in a way that can catalyze change in urban systems.

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Labs, thank you for your guidance and support along the way. And to the greater research community working to decarbonize the building sector, thank you for all you do, I hope our collective efforts will make a difference for future generations.

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Chapter 1. Introduction and Background

Extreme heat and wildfire are becoming more prolific and exacerbated by climate change, carrying significant implications for environmental and social systems. In urban areas, residential buildings provide refuge from climatic events, offering protection from extreme weather and access to mitigation technologies such as cooling and air cleaning. Housing constructed to be both energy efficient and resilient provides the most protection by increasing thermal safety for occupants and minimizing the energy resource consumption of the building (Martel, 2016; Mills, 2003). However, the building sector is a major contributor to greenhouse emissions; consuming 39% of total energy in the United States, 20% of which is attributed to residential buildings (U.S. Energy Information Administration, 2018), translating to approximately 229 metric tons of CO_2 equivalent in 2016 (U.S. EPA, 2019). Residential buildings built before the U.S. Department of Energy's (DOE) Building Energy Codes Program was established in 1992 represent approximately 68% of residential building stock in the country. These homes are energy-intense, and often have significant air leakage, inadequate insulation, and inefficient heating and cooling systems leading to substantial environmental footprints (Livingston, Elliott, Cole, & Bartlett, 2014). Additionally, these older, inefficient homes increase heat and pollutant exposure risk to occupants due to leaky thermal enclosures, poorly operating heating, ventilation and air conditioning (HVAC) systems and lack of air conditioning (Cardona et al., 2012; William J Fisk, 2000). The recent advancement of climate-driven extreme heat and wildfire events, coupled with the need to curb emissions has underscored the urgency for an energy efficient, resilient building stock.

Climate change causes increases in severity and frequency of extreme weather events, such as heat, drought, and risk for wildfire (Luber & McGeehin, 2008). Residential buildings play an integral role in risk management strategies by providing a climate-resilient infrastructure that allows people to shelter-in-place during extreme events, minimizing the risks of exposure during the response and recovery period post-disaster (Ebi et al., 2021). Yet, heat vulnerability indices often exclude housing characteristics such as thermal efficiency, which can be a key determinant of vulnerability (Samuelson et al., 2020). The residential building sector is highly variable in terms of technology access, efficiency, and energy intensity, all of which impact the risks associated with heat and pollutant exposure for occupants that reside within them. Exposure risks related to urban heat, wildfire woodsmoke and socio-economic status along with the role that residential buildings play in climate resiliency are a central focus of this dissertation.

Exposure Risk and Extreme Urban Heat

Urban areas experience two primary heat situations. The first is extreme heat, which is a result of increased temperatures for prolonged periods of time, relative to regional averages. The second are urban heat islands (UHI's), which are the presence of hotter areas throughout the city, characterized by landscape factors such as tree canopy, parks and open spaces and bodies of water, along with hardscape factors in the built environment, such as buildings, pavement and infrastructure (Mohajerani, Bakaric, & Jeffrey-Bailey, 2017). Both heat situations increase heat exposure risk for people inside their homes, a serious health risk that can lead to illness and mortality (Quinn et al., 2014).

In the urban environment, UHIs are becoming more prolific and exacerbated by climate change. UHIs are traditionally characterized by observed increased temperature in urban areas, compared to rural areas (Arnfield, 2003). However, the true heat distribution includes the presence of microthermal extremes and anomalies which describe areas within the urban landscape that present additional temperature variation (Moffett, Makido, & Shandas, 2019). A rapidly growing body of evidence suggests that air temperatures within a metropolitan region can vary by as much as 11°C (20°F) in ambient temperatures, causing the presence of UHI's on micro-scales, rather than the traditional urban/rural divide (Klok, Zwart, Verhagen, & Mauri, 2012; Shandas et al., 2019). Therefore, not only do UHIs exist in cities, but the location and spatial distribution of them can vary greatly throughout urban areas. This is an imperative topic that relates specifically to the spatial distribution of energy use in residential buildings, and includes interactions among landscapes, technologies, and energy flows. Socio-demographics and behavioral factors further complicate the distribution of UHI, as they both influence the spatial layout of the city and energy use in buildings.

Heat exposure presents significant health risks to urban inhabitants. Heat exposure can lead to heat exhaustion, syncope, reduced sleep quality and cognitive performance, and exacerbates existing respiratory, renal and cardiovascular issues and in extreme cases, death (Kenney, Craighead, & Alexander, 2014; Kilbourne, 1997; Laurent et al., 2018; Obradovich, Migliorini, Mednick, & Fowler, 2017; Remigio et al., 2019).

Additionally, chronic heat exposure can lead to early mortality (Wallace, Kriebel, Punnett, Wegman, & Amoroso, 2007). As extreme heat events increase, UHIs also become more intense. Studies have shown that UHIs present a higher mortality risk for people living within them (Tan et al., 2010; Taylor et al., 2015; Tomlinson, Chapman, Thornes, & Baker, 2011). Furthermore, systemic racism and exclusionary housing policies have amplified the exposure risks for low-income, and communities of color who often live in the hottest areas of a city and have less access to air conditioning in their homes (Hoffman, Shandas, & Pendleton, 2020).

Mitigation strategies are necessary to protect people, especially vulnerable populations from heat risk. Urban greenspace and vegetation have been shown to mitigate temperature in a number of studies (Dimoudi & Nikolopoulou, 2003; Irga, Burchett, & Torpy, 2015; Makido, Shandas, Ferwati, & Sailor, 2016; Voelkel & Shandas, 2017). Cool coatings, used on building roofs and exterior walls also reduce solar reflectance, thus lowering the surrounding ambient temperature (Synnefa, Santamouris, & Apostolakis, 2007; Zinzi & Agnoli, 2012). UHIs also contribute to air quality issues by increasing ground level ozone, which can result in increased levels of volatile organic compounds and nitrogen oxide in areas within UHIs (Lo & Quattrochi, 2003; Sarrat, Lemonsu, Masson, & Guedalia, 2006). Residential buildings play an important role in heat mitigation, and resilient housing that is both energy efficient and provides refuge from the heat can help lower the exposure risks associated with urban heat.

Exposure Risk and Indoor Air Quality

Recent decades have been marked by increased concern about our indoor environments related to the quality of indoor air and pollutant exposure. The average American spends 90% of their day indoors, where exposure to pollutants can be higher than outdoors (US EPA, 2018). The lack of regulation of pollutant concentrations in the indoor environment means that occupants may be subject to significant exposure risks without being aware of it. The health consequences are not trivial; there is robust literature that has found direct linkages between indoor pollutant exposure and health, including ailments such as general irritation, headaches, dizziness, fatigue, respiratory diseases, heart disease, cancer and premature death (Dales, Liu, Wheeler, & Gilbert, 2008; Jones, 1999; Sundell, 2004; Tham, 2016; US EPA, 2018; Wolkoff, 2018; World Health Organization, 1989). These observations have been made without considering factors that would cause pollutant concentrations to increase, such as increases of particulates from woodsmoke, caused by wildfire. Nazaroff (2013) noted that climate change will increase the need for ventilation, filtration, and air cleaning because of degraded IAQ due to elevated indoor pollutant concentrations. However, older building stock throughout the country rarely has adequate ventilation and building codes in many regions do not require air quality assessments or ventilation approaches to ensure air quality indoors, such as *ASHRAE Standard 62.2: Ventilation and Acceptable Indoor Air Quality in Residential Buildings*.

The frequency and scale of wildfire events throughout world continue to increase. Climate change is a major culprit, increasing the potential for wildfires, especially large-scale, megafires (Barbero, Abatzoglou, Larkin, Kolden, & Stocks, 2015; Yongqiang Liu, Stanturf, & Goodrick, 2010). In the Pacific Northwest, climate change is increasing outdoor particulate matter concentrations through extreme heat and wildfire events (Geiser & Neitlich, 2007). During wildfire events large amounts of woodsmoke is released, comprised of particulate matter, carbon monoxide, ozone, volatile organic compounds (VOCs), as well as other compounds such as polycyclic aromatic hydrocarbons and benzene (Altshuler et al., 2020; Elliott, 2014). Prior studies have found that exposures to wildfire smoke increase mortality risk, respiratory illness, and cardiovascular mortality (Anjali et al., 2019; Johnston, Hanigan, Henderson, Morgan, & Bowman, 2011; J. C. Liu, Pereira, Uhl, Bravo, & Bell, 2015; Richardson, Champ, & Loomis, 2012).

A recent case study in Washington state found that $PM_{2.5}$ levels increased significantly indoors during a wildfire event (Kirk et al., 2018). In low-income homes, $PM_{2.5}$ concentrations increased by as much as 4.6 times compared to outdoors as a result of wildfire plumes (Shrestha et al., 2019). Another recent study in Australia found that remaining indoors during wildfire events does protect occupants from exposure, but the level of protection is highly variable and dependent on housing characteristics and ventilation (Reisen, Powell, Dennekamp, Johnston, & Wheeler, 2019). In one study, properly sized air cleaners were shown to decrease $PM_{2.5}$ by as much as 63-88% compared to homes without (Henderson, Milford, & Miller, 2005), and modeled reductions in indoor $PM_{2.5}$ concentrations have been estimated to be as much as 31% (Huang et al., 2021).

Public health officials encourage residents to keep windows closed and use portable air cleaners during high smoke days to offset impacts of smoke inhalation (Barn et al., 2016; Henderson et al., 2005). One study looked at potential impacts of wildfire interventions that included combinations of forced air system operation, filtration and air cleaners on health, finding that interventions could decrease both hospital admissions and deaths attributed to wildfire smoke (Fisk and Chan 2017). However, a baseline understanding about residential IAQ during wildfire is not well understood.

There is a need to better understand the complex interaction among indoor air quality, energy use and exposures caused by a changing climate for several reasons. First, during high heat and smoke events, people are encouraged to remain indoors with windows closed to keep smoke exposure low, meaning that air conditioning, filtration and mechanical ventilation will be necessary to maintain thermal comfort and IAQ, which introduces a feedback between energy efficiency and IAQ. Second, the complex chemical makeup of wildfire can include a toxic array of chemicals and particulate matter ranging from PM, ozone, carbon monoxide, polycyclic aromatic compounds and nitrogen oxides (Zachary et al., 2019) and while these pollutants are known and studied, the release of them in wildfire events differs from other modes of emissions and there does not exist loss mechanisms associated with HVAC operations. Finally, it has been hypothesized that the health effects of climate change will be realized through indoor exposures (Fisk, 2015; Nazaroff, 2013), highlighting the need to better understand the risks and potential mediations of heat and wildfire on indoor environments.

Exposure Risk and Low-Income Households

Traditionally in the residential building sector, energy poverty and energy insecurity are terms that have been used to describe the inability of a household to meet their basic energy needs (Bednar & Reames, 2020; Day, Walker, & Simcock, 2016). Energy insecurity might come down to the need for a household to choose between paying an energy bill over another expense or a sacrifice on comfort, such as limiting or forgoing air conditioning in a hot or humid climate. A third crosscutting term, energy justice, refers to equitable distribution of energy resources (Bouzarovski, 2018; Jenkins, McCauley, Heffron, Stephan, & Rehner, 2016), and allows for the traditional characterization of underserved populations to include environmental racism. Many low-income, Black, Hispanic and Native American families live in older, less efficient housing and experience energy insecurity (Drehobl, Ross, & Ayala, 2020). Communities of color and low-income households have been shown to spend a disproportionate amount of income on electric and gas utilities, and can be more heavily impacted by exposure from extreme weather events (Drehobl et al., 2020; Hernández & Bird, 2012; Langevin, Gurian, & Wen, 2013; Tony Gerard Reames, 2016b; Sakka, Santamouris, Livada, Nicol, & Wilson, 2012). Energy insecurity has been tied to poor respiratory and mental health (Hernández & Siegel, 2019), and is felt more by communities of color (Memmott, Carley, Graff, & Konisky, 2021).

Risk is at the center of human interaction with climate and is an important term to define when considering the impacts of energy burdens. Risk can be related to an acute condition, such as exposure to extreme temperatures during a heat wave, or chronic conditions such as increased energy burdens caused by inefficient housing. Extreme weather and climate events impact populations in disproportionate ways, with communities of color more heavily impacted than white populations (Uejio et al., 2011). The amount of exposure risk depends on the vulnerability of a population; and vulnerability can vary dramatically due to economic, social, geographic, demographic, cultural, institutional, governance, and environmental factors (Cardona et al., 2012). The Intergovernmental Panel on Climate Change (IPCC) identifies that "risk of climate-related impacts results from the interaction of climate-related hazards (including hazardous events and trends) with the vulnerability and exposure of human and natural systems" (IPCC Working Group II, 2014). Climate impact risk are compounded by the energy insecurity and high energy burdens that low-income households already face on a regular basis.

Extreme heat and poor air quality are exacerbated by acute climate events such extreme heat and wildfire, which can increase mortality rates (Azhar et al., 2014; Huynen, Martens, Schram, Weijenberg, & Kunst, 2001; Mitchell et al., 2016; Samet, Dominici, Curriero, Coursac, & Zeger, 2000; West et al., 2013). As noted above, the distribution of heat on a city-scale is disproportionately felt by low-income areas. For example, one study found higher instances of heat distress and heat mortality in low-income neighborhoods, specifically those with higher minority and socially isolated populations, and vacant lots (Uejio et al., 2011). The presence of heat islands are more intense for low-income neighborhoods subject to discriminatory housing policies, where a disproportionate number of households are exposed to extreme heat (Hoffman et al., 2020; Voelkel, Hellman, Sakuma, & Shandas, 2018). Systematic racism has also been connected with lower density of trees and greenspaces, further increasing heat risk for low income and communities of color (Schell et al., 2020). These chronic conditions related to energy in housing is a potential compounding factor when considering the impacts of climate change, specifically those related to exposure risks associated with heat and air quality.

Energy efficiency programs have long targeted existing housing stock throughout the country to increase energy efficiency in older, underperforming homes and are common policy instruments used to weatherize the low-income housing stock. Energy efficiency programs can help reduce utility bills, improve comfort and increase the efficiency of the housing stock (Drehobl and Ross, 2016). It has been estimated that retrofitting older homes could reduce U.S. residential building energy use by as much as 34% and carbon emissions by 35% (Nadel, 2016). The U.S. Department of Energy's (DOE) Weatherization Assistance Program (WAP) provides grants to states and governmental organizations to weatherize low-income homes. Grantees manage a network of 900+ local weatherization agencies that include state energy offices, community action agencies, nonprofit organizations, and local government agencies that are eligible to receive DOE funding. The American Recovery and Reinvestment Act of 2010 significantly increased WAP funding over a period of 5 years. Recent analysis of the costs and benefits of WAP indicate the program saved 9.9 trillion Btus and $1.6 billion in energy cost savings in program years 2008-2010 (Tonn, Rose, & Hawkins, 2018). Critics of WAP maintain the program costs outweigh the benefits, and that projected savings is overstated (Fowlie, Greenstone, & Wolfram, 2018). Regardless, barriers associated funding and regulatory challenges exist, that results in long waitlists, high deferral rates and issues with overall program efficiency (Raissi & Reames, 2020).

In addition to WAP, utility bill assistance programs are funded federally through the Low-Income Home Energy Assistance Program (LIHEAP), HUD, and USDA housing assistance programs. These programs provide direct subsidies to income qualified households to cover energy costs, and make up about 80% of all expenditures in low-income energy programs (Brown, Soni, Lapsa, Southworth, & Cox, 2020). Subsidies are an important mechanism for managing chronic energy insecurity for households in need. However, program requirements such as asset tests limit participation, especially for the lowest-income households (Graff & Pirog, 2019), and LIHEAP benefits are not likely to cover all primary fuel bills (Bruce Tonn, Schmoyer, & Wagner, 2003). There is also the issue of the "split-incentive" where landlords with tenants who pay their utility bills will underinvest in energy efficiency measures, which is often felt the most by low-income tenants (Bird & Hernández, 2012; Melvin, 2018).

Conceptual Framework and Research Questions

Research for this dissertation focused on the interactions among people, the homes they live in and the implications of climate change, specifically extreme heat, and wildfire. To frame the focus of study, a framework was developed to capture the impacts of climate change and vulnerability in urban residences, associated with exposure risk from heat and woodsmoke from wildfire. The framework set forth is an adaptation of the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report's vulnerability framework, along with subsequent iterations focusing on climate change impacts and sustainability (O'Lenick et al., 2019; B. C. O'Neill et al., 2014; Oppenheimer et al., 2015).

Figure 1 outlines a high-level, descriptive framework that is the basis for the investigation included in this dissertation, with exposure risk presented centrally related to three primary factors: the built environment, personal vulnerability, and individual behavior. Additionally, external climate and social factors impact any one person's ability to adapt, endure and mitigate exposure. Climate factors include acute hazards such as extreme heat and wildfire, along with natural climate variability and climate change. Social factors integrate human connections with the built and natural environment and consider how different populations experience and perceive their individual realities of risk. These social factors include differences in experience based on socio-demographics (e.g., where a person can afford to live), the impacts of energy equity (e.g., differences in energy burdens), the influence of urban form (e.g., the location of a household relative to heat islands), and the ability to access and utilize technologies that mitigate exposure (e.g., air conditioning, air cleaning).

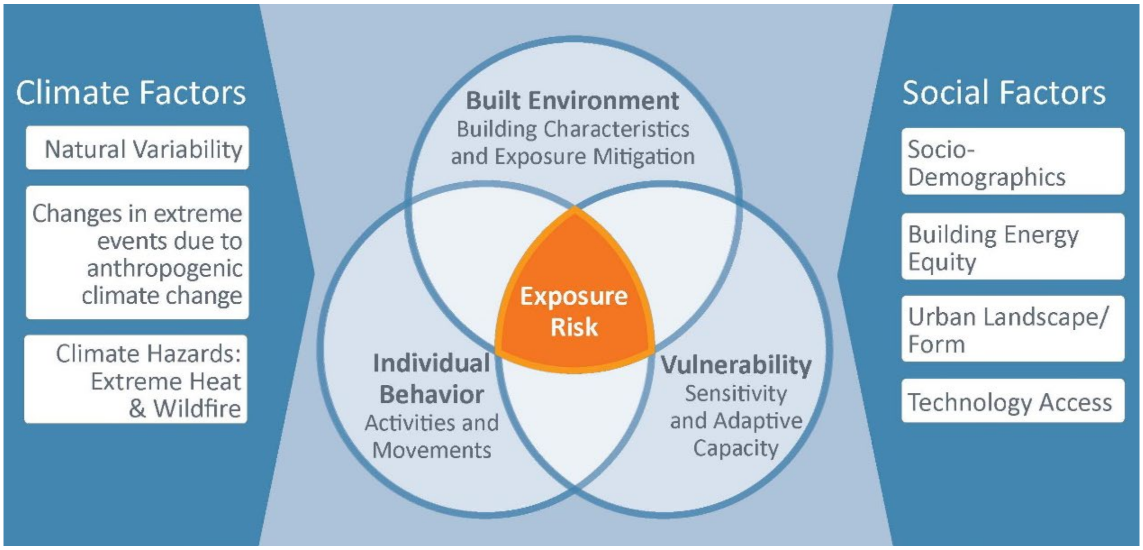

Figure 1. Conceptual framework for investigating residential occupant exposure risk associated with extreme heat and woodsmoke from wildfire. (Adapted from Oppenheimer et al. 2015; O'Lenick et al. 2019; O'Neill et al. 2014).

The research in this dissertation includes many connections among factors but is not attempting to be comprehensive in linkages relative to Figure 1. For example, the influences that are increasing the frequency and duration of extreme heat and wildfire are not explored. Similarly, the underlying factors that create unjust energy systems are not explored, but the residential-scale impacts of energy equity are. Specific overarching research questions explored in this dissertation include:

1. On a city-scale, what are the relationships between increased ambient heat, building characteristics and energy use? How do these relationships vary on a spatial scale based on location within a city?

2. How do residential building characteristics and technology interventions impact exposure to heat and woodsmoke during extreme heat events and wildfires?

3. How do building characteristics, energy burdens and income impact exposure risk in residential buildings, and how are different populations impacted? How do these interactions impact equity and justice in residential energy systems?

The research explored within addresses several significant gaps in current knowledge. First, city-scale urban heat vulnerability is a known issue, but there is a lack of understanding about the role that individual building attributes, such as envelope and mechanical system performance, have on occupant vulnerability to heat exposure. All three papers investigate the impacts that building attributes have on indoor exposure risk. Furthermore, the impacts of wildfire events on indoor air quality, and the performance of residential building technologies is not well understood. This dissertation provides assessment of indoor air quality and performance during a large wildfire event. Finally, energy burden calculations often miss the nuanced impacts of chronic energy insecurity caused by inefficient housing. The work explored within looks at individual building attributes that contribute to high energy burdens in low-income housing.

There is a myriad of ways that individuals can be exposed to extreme heat and degraded air quality caused by climate-induced hazards. This research is focused specifically on exposures related to the built environment, more specifically, the homes people live in. Chapter 2 explores ambient heat and presence of air conditioning throughout the city of Portland, OR. Chapter 3 investigates the indoor air quality of a residential building during a large wildfire event in 2020 and models the air quality impacts of proposed mitigation methods. Figure 2 presents a high-level framework used for both investigations, focused on how the ambient environment (e.g., ambient temperature and air quality) impacts the energy use in a household, considering a variety of influences that will also be contributing factors including urban form, building characteristics and socio-demographics.

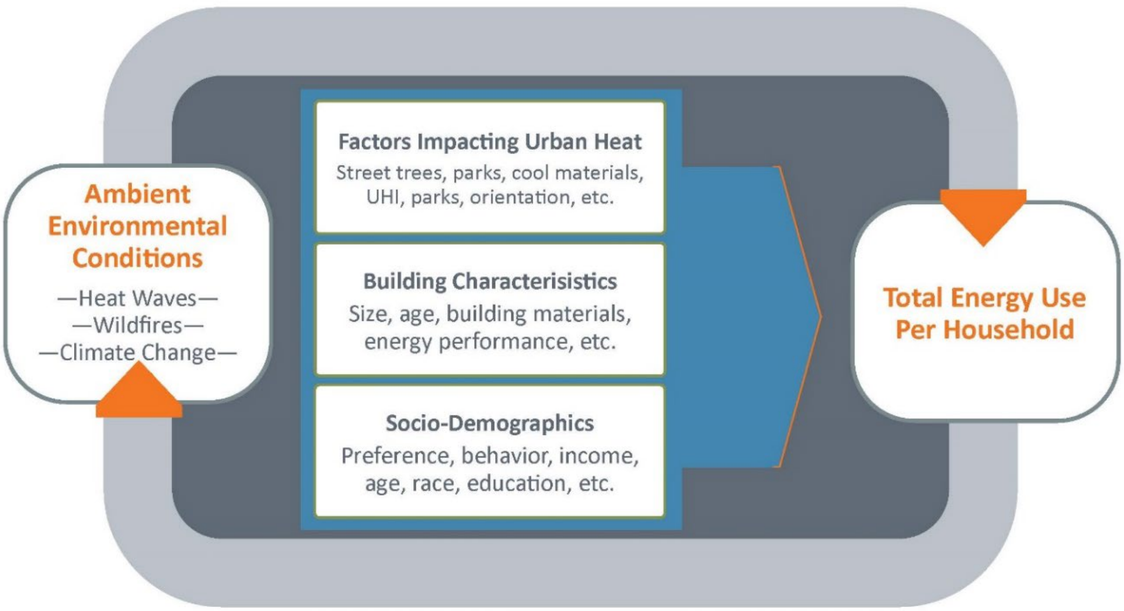

Figure 2. Conceptual framework describing the relationship between the ambient urban environment and residential building energy use.

But to investigate the human-focused experience in homes and the associated risks, it is important to include social constructs and societal factors that may influence individual behavior and experience. These factors are considered specifically in this dissertation work in Chapter 4, where energy burdens, equity and sociodemographic themes related to building energy use and performance are explored. Chapter 4 explores equity impacts associated with climate change and the built environment. There is robust literature pointing to the disproportionate impacts that both energy use and urban heat has on low-income communities (Hernández & Bird, 2010; Hoffman et al., 2020; Harlan et al., 2007; Memmott et al., 2021; Sakka et al., 2012; Schell et al., 2020; Sherwin &

Azevedo, 2020; Shrestha et al., 2019). Figure 3 identifies the primary barriers low-income and vulnerable households experience related to the conceptual framework presented in Figure 1. These barriers highlight the connections of the framework categories to vulnerable populations. The analysis presented in Chapter 4 focuses on energy equity and burdens in low-income homes versus the general population of housing in Portland, OR identifying trends in building characteristics, location, and equity.

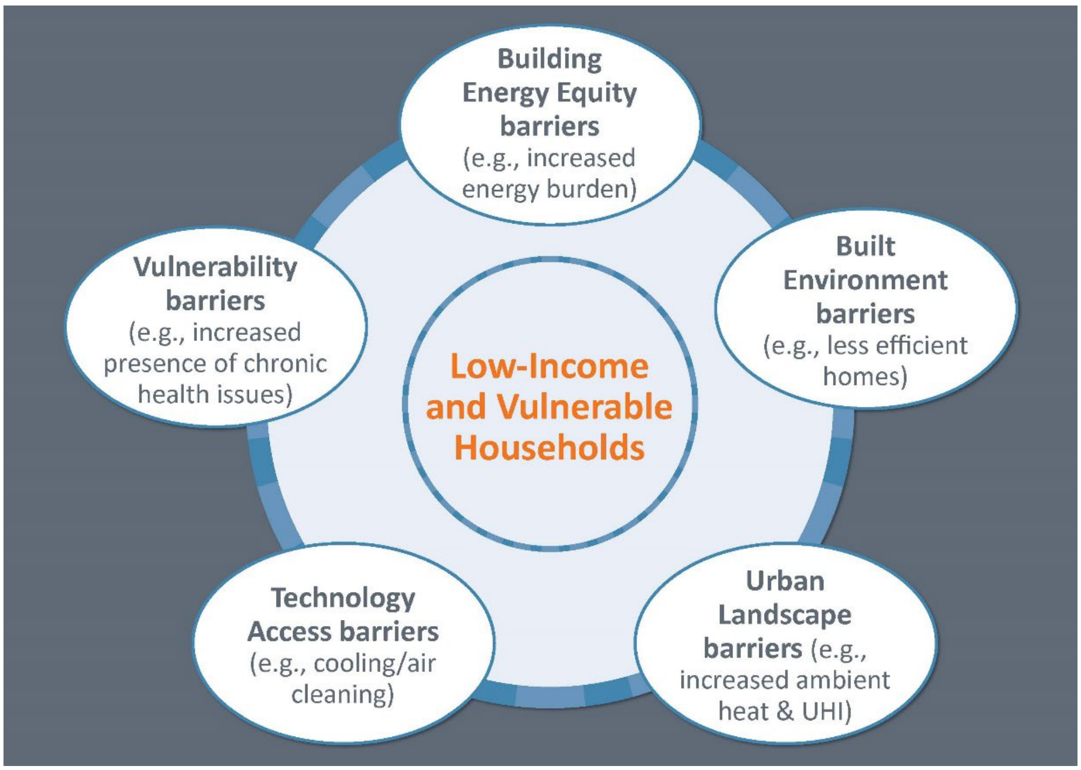

Figure 3. Equity barriers present in low-income and vulnerable households.

Study Area Geography and Impacts of Climate Change

This study is focused on the climate change impacts in the Pacific Northwest (PNW), using the city of Portland, OR as an urban study area. The Pacific Northwest is typically considered to include a portion of British Columbia, and the entirety of

Washington, Oregon, and Idaho. In Oregon, the Portland Metropolitan Area (PMA), located at the north end of Oregon's Willamette Valley, is the state's most densely populated area. The PMA is comprised of three counties and 24 cities, concentrated around Portland, Oregon, the largest city. The city sits just above sea level and is located at the confluence of the Willamette and Columbia rivers, in between the Cascade and Coastal mountain ranges. The average temperature ranges from 40.4°F (4.7°C) in December to 69.5°F (20.8°C) in August (NOAA, 2017). The International Energy Conservation Code (IECC), a model building code designed to guide residential and commercial construction to meet energy efficiency standards, designates climate zones to inform best practices in energy-efficient building construction, which are broken down to include both temperature and moisture designations. The PMA is designated as 4C, indicating a marine climate, characterized by mild winters, moderately dry summers and moderate humidity levels which translates to climate "Csb" on the Köppen-Geiger climate map (International Code Council, 2018; Kottek, Grieser, Beck, Rudolf, & Rubel, 2006). The marine influence on the Willamette Valley has traditionally kept the region mild, resulting in lower rates of installed air conditioning compared to other regions.

Climate change is quickly altering the regional environment, causing incidences of extreme events to increase. The 2020 fire season was one of the most destructive in history, resulting in at least 11 deaths directly caused by fire and many more due to exposure and poor air quality, and burning over one million acres, including thousands of homes (Northwest Interagency Coordination Center, 2020). In June 2021, the region experienced an unprecedented extreme heat event which lasted for multiple days, with the PMA reaching temperatures of 116°F (46.7°C), a phenomena that would have been impossible without the impacts of human-caused climate change (Philip et al., 2021). Analysis of Pacific Northwest using global climate models have predicted warming in the next 50 years to average between 0.2-1.0°F (0.1-0.6°C) per decade, possibly reaching 5.3°F (3.0°C) by the 2080's (Mote, Salathe, Duliere, & Jump, 2008; Mote & Salathé, 2010). The Pacific Northwest relies on snowpack for summer waterflows throughout the region. Snowpack levels were measured throughout the region in one study between 1950-2000, finding that in some cases the decrease was in excess of 40%, an indicator of the warming climate in the PNW (Mote, 2003). Further study has found that for every 1°C warming, peak snow water equivalent will decline by 22%-30% (Cooper, Nolin, & Safeeq, 2016), disrupting downstream ecosystems and exacerbating effects of climate change.

Wildfire instance and severity trends closely to the change in temperature and precipitation in the PNW. In Portland, the Department of Environmental Quality (DEQ) has monitored the wildfire smoke impacts on outdoor air quality, measured by the Air Quality Index (AQI), since 1985. Prior to 2015, there were no days marked "unhealthy for sensitive groups," "unhealthy," "very unhealthy," or "hazardous" in the PMA caused from wildfires. Between 2015-2018, 14 days were recorded as "unhealthy for sensitive groups" or higher (Oregon Deaprtment of Enviornmental Quality, 2019). These 14 days are related directly to wildfire smoke. In 2020, during the worst fire season in history, the PMA recoded 9 days above "unhealthy for sensitive groups" with a record 6 days classified as "hazardous" (Oregon Department of Environmental Quality, 2021). The number of ignitions has remained relatively stable since 2008, however, the total acreage of fires in the Pacific Northwest has increased dramatically. In the 2018 fire season, 901,613 acres in Oregon, and 438,868 acres in Washington burned totaling almost 1.5 million acres, up from about 200,000 combined in both states during the 2008 fire season (U.S. Bureau of Land Management, 2018). In 2020, close to 5 million acres burned in Oregon, Washington, and Northern California (Oregon Department of Environmental Quality, 2021).

Researcher Positionality

The research presented in this dissertation is closely tied to my personal and professional experiences and positions. Personally, I care deeply about advancing scientific research that will decrease the impacts of climate change on environmental and social systems. Additionally, I feel that the benefits of scientific advancement should be equitably distributed throughout social systems, and to truly benefit society, we must correct institutional inequities. In my role as a researcher at the Pacific Northwest National Laboratory, I have been exposed to different approaches, whether technology-focused or program-focused, aimed at reducing energy consumption of the built environment, and for the past eight years, in residential buildings. Through these exposures I have observed first-hand how technology diffusion occurs in an inequitable fashion throughout society. When I was initially introduced to green technologies in buildings, along with green building design and construction, it was immediately apparent that these technologies and approaches were only available to a select few that could afford the extra steps/materials/technologies required to construct or renovate net-zero homes. As my career and education progressed, I realized how these high-end market technologies would make the most impact if they were installed in homes in traditionally underserved communities, and I became focused on trying to figure out ways to diffuse green buildings into low-income housing. I hope that I can contribute towards an energy future focused on justice and equity in energy-systems. I approached this research as a person focused on advancing scientific knowledge about the impacts of extreme heat and woodsmoke in residential buildings, but also as an advocate for environmental/energy justice for low-income and underserved communities.

I approached data-gathering and analysis aware of my personal bias and strived to draw conclusions without judgement. I would be remiss to note I am a white woman, living and working in an urban environment that is not very diverse; my approaches to this work are undoubtedly shaped by this experience and reality. While acknowledging this, my work is focused on exploring ways communities can implement equitable strategies towards climate change resilience that include zero-energy, efficient buildings. I feel strongly about using my scientific endeavors to better our society and strive to learn from my worldly experiences.

For much of the applied research presented in this dissertation, I have opted to use the term “we” instead of “I” when describing methods and results. One reason for this is because I have been formally trained in scientific writing, where the norm is to write in the third person. But I also opted to use this voice as a way to acknowledge my colleagues, mentors and friends who all advised me throughout this process and helped bring this research to its final form.

Format of the Dissertation

This dissertation develops three journal-length papers focused on related aspects of climate change, residential buildings an occupant exposure, as discussed above. Some of the literature review presented in Chapter 1 is also included in the introduction sections of related papers. Chapter 2 presents the first paper "*Analyzing the city-scale distribution of ambient temperatures, air conditioning and building characteristics in residential buildings,*" which investigates the presence of air conditioning and building energy characteristics relative to the location of heat islands in the city of Portland, OR. Chapter 3 details the second paper "*Experimental assessment of interventions to reduce $PM_{2.5}$ in a residence during a wildfire event,*" reporting results of a physical experiment and modeling exercise of indoor and outdoor particulate matter concentrations during an extreme wildfire event in 2020 and the influences of intervention measures. Chapter 4 presents the third paper "*Housing inefficiency and energy poverty: How building characteristics impact energy burdens in low-income housing*" which investigates factors that contribute to energy burdens in a large sample of homes throughout Portland, and a subset of low-income homes participating in a local energy-efficiency program. Chapter 5 is the conclusion of the dissertation, which, like the literature presented in the introduction, links the three papers' thematically, and explores collective findings, limitations and future research opportunities related to climate change and the residential building sector.

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Chapter 2. Analyzing the City-Scale Distribution of Ambient Temperatures, Air Conditioning and Building Characteristics in Residential Buildings

Introduction

Extreme heat events continue to emerge as serious threats to urban and social systems. Extreme heat from heat waves are the biggest cause for mortality in many cities and responsible for more deaths annually than any other form of extreme weather (Luber & McGeehin, 2008). A recent study found that 37% of heat-related deaths are attributed directly to climate change, and that increased mortality is directly related to warming throughout the world (Vicedo-Cabrera et al., 2021). In the Western United States, years of drought and increased temperatures have triggered wildfires and extreme heat events, resulting in serious environmental, health and infrastructure risks. Exposure to extreme heat is a public health threat that is expected to increase as climate change is exacerbated, especially in urban areas (Habeeb, Vargo, & Stone, 2015). Access to air conditioning (AC) during heat waves is an important mitigation strategy for heat exposure, but power outages during extreme heat events may further complicate access to cooling (Stone et al., 2021).

In the urban environment, the uneven distribution of ambient temperatures creates urban heat islands (UHI), which are also becoming more prolific and exacerbated by climate change. UHIs are traditionally characterized by observed increased temperature in urban areas, compared to rural areas (Arnfield, 2003). However, true heat distribution within a city includes the presence of microthermal extremes and anomalies which describe areas within the urban landscape that present additional temperature variation

(Moffett et al., 2019). A rapidly growing body of evidence suggest that air temperatures within a metropolitan region can vary by as much as 11 °C (20 °F) in ambient temperatures, causing the presence of UHIs on micro-scales, rather than the traditional urban/rural divide (Klok et al., 2012; Shandas et al., 2019). Vulnerable communities are disproportionately exposed to UHI, with low-income neighborhoods more likely to be located in hotter areas of the city (Hoffman et al., 2020; Wilson, 2020). Furthermore, elderly, minority and low-income communities have higher mortality risks associated with extreme heat (Hondula, Davis, Saha, Wegner, & Veazey, 2015). In addition to heat-related health risks, UHI's contribute to air quality issues by increasing ground level ozone, which can result in increased levels of volatile organic compounds and nitrogen oxide in areas within UHI's (Lo & Quattrochi, 2003; Sarrat et al., 2006). Strategies to decrease UHI on an urban scale include limiting exposed concrete, increasing greenspace and parks, planting trees, and green roofs (Bowler, Buyung-Ali, Knight, & Pullin, 2010). Like other climate-change mitigation approaches, the middle class and wealthy tend to benefit more from such initiatives (Haase et al., 2017).

During extreme heat events, access to AC provides increased thermal comfort, and for many at-risk populations is necessary to mitigate heat-related illness and mortality in homes (Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2016). As temperatures and incomes rise throughout the world, residential AC installations are expected to increase (Davis & Gertler, 2015), which could increase electricity consumption by as much as 42% in homes (Randazzo, De Cian, & Mistry, 2020). Widespread use of AC, particularly in urban areas, places a significant burden on electricity infrastructure, increasing risk of power outages and fires (Burillo, Chester, Pincetl, & Fournier, 2019). Additionally, access to AC is disproportionate in urban areas, with wealthier neighborhoods more likely to install AC, and low-income households forced to endure the heat, or fall into energy poverty (Randazzo et al., 2020). One study found that deaths among African Americans were more likely to be associated with extreme heat, and presence of AC was less than half of white households in the same city (O'Neill, Zanobetti, & Schwartz, 2005).

Increased extreme heat events and UHIs also have impacts on building energy use. A recent survey of extant literature on the subject determined that UHI could result in an increase of 19% in cooling loads and a decrease of 18.7% in heating loads (Li et al., 2019). It is important to note that the metric used for measuring UHI, such as air temperature or land surface temperature, along with the method (remote sensing vs other), is an important distinction that will measure different impacts on energy use relative to UHI (Deilami, Kamruzzaman, & Liu, 2018a). Most studies are results of modeling exercises (Guattari, Evangelisti, & Balaras, 2018; Yuezhong Liu, Stouffs, Tablada, Wong, & Zhang, 2017; Zinzi & Carnielo, 2017), or have only utilized one temperature weather station (usually at an airport) to distinguish the urban vs. rural temperature (Li et al., 2019). Two studies that took more than one rural temperature datapoint (both from two airports as opposed to one) found significant intra-urban variations on modeled UHI impacts on building energy use (Guattari et al., 2018; Street, Reinhart, Norford, & Ochsendorf, 2013), highlighting the limitations of determining building energy use using only one temperature datapoint.

This study builds off previous studies, looking specifically at the presence of air conditioning and energy efficiency relative to the location of urban heat. Using statistical and spatial analyses, and a granular dataset that includes data for over 16,000 single-family residential buildings coupled with detailed temperature data in Portland, Oregon, we ask the following research questions:

1. To what extent are homes with AC located in the hottest parts of town?
2. How does energy use differ in homes with AC and what factors are present to explain any observed difference?
3. What is the spatial relationship between ambient temperature and residential building characteristics?

Methods

This study uses a combination of statistical and spatial analyses, described below.

Study Area

The city of Portland, Oregon is the focus of this study. The City is the most populated metropolitan area in Oregon and one of the larger cities on the west coast of the U.S. The average temperature ranges from 4.7 °C (40.4 °F) in December to 20.8 °C (69.5 °F) in August (National Oceanic and Atmospheric Administration, 2017). The residential sector is dominated by single-family detached residential buildings, which is the focus of this study. The city is considered a marine climate, categorized by mild winters, dry summers and moderate humidity levels, which translates to climate "Csb" on the Köppen-Geiger climate map (Kottek et al., 2006).

Data

To identify building characteristics, energy use, greenhouse gas emissions and energy cost, we used a novel dataset from the U.S. Department of Energy's (DOE) Home Energy Score program, which for this analysis, includes energy data from 12,369 single family homes in Portland, Oregon. The DOE Home Energy Score (HES) program was launched in 2012 to provide a low-cost alternative to full existing home energy audits, similar to gasoline efficiency ratings for a car. The HES is targeted to homeowners and homebuyers as a simple way to understand the energy performance of a building. To determine a HES, a trained third party assessor enters building characteristics into a software tool which then runs an algorithm using the E+ building energy modeling tool (U.S. Department of Energy, 2017). The "Score" is designed to provide an overview of the home's energy performance, based on the building inputs added to the tool.

The City of Portland, Oregon has a large sample of HES due to a city-wide program enacted in 2016. The program requires nearly every home seller within the City of Portland limits to include the Home Energy Score and Report in any listing or public posting about the home that becomes available to homebuyers. The program uses the HES as an analysis tool to identify energy savings opportunities and to provide guidance regarding efficiency measures that will save the most energy and cost for occupants. The scores used here were taken between 2018-2020 and mirror the real-estate market, providing data regardless of socio-economic factors. Variables and spatial attributes studied include a combination of home characteristics, energy metrics and HVAC performance (Table 1).

Table 1. Data inputs included in HES database, used for this study.

Home Characteristics	Address/location Year built Conditioned floor area
Energy Metrics	Energy use intensity Energy use (kwh/therms) Energy cost Greenhouse gas emissions
HVAC Characteristics	Heating system type Cooling system type HVAC efficiency Fuel type

To understand the role of urban air temperature and presence of air conditioning on residential energy use, we appended values from a dataset that describes summer air temperatures, sampled on a hot day to the HES dataset. The temperature dataset consisted of average morning, afternoon and evening air temperatures that were based on an established protocol, and used in previous study (Antonopoulos, Trusty, & Shandas, 2019; Voelkel et al., 2018). The method for describing temperatures across the study area consisted of collecting approximately 50,000 location-specific temperature readings during one day of an extreme heat event on 25 August 2016, in Portland, Oregon, when the average temperature during the hottest hour of the day was in the 90th percentile of 30-year historic daily temperatures for the study region. Temperatures were sampled for one hour at 3 times during the day (6 a.m., 3 p.m., and 7 p.m.) using vehicle traverses (cars with a mounted temperature sensor and global positioning system (GPS)) in nine predetermined sections of the city. The temperatures were translated to raster files (Figure 1), and the associated morning, afternoon and evening temperature values from the data raster were appended to each HES datapoint, which represents one residential building in Portland, Oregon.

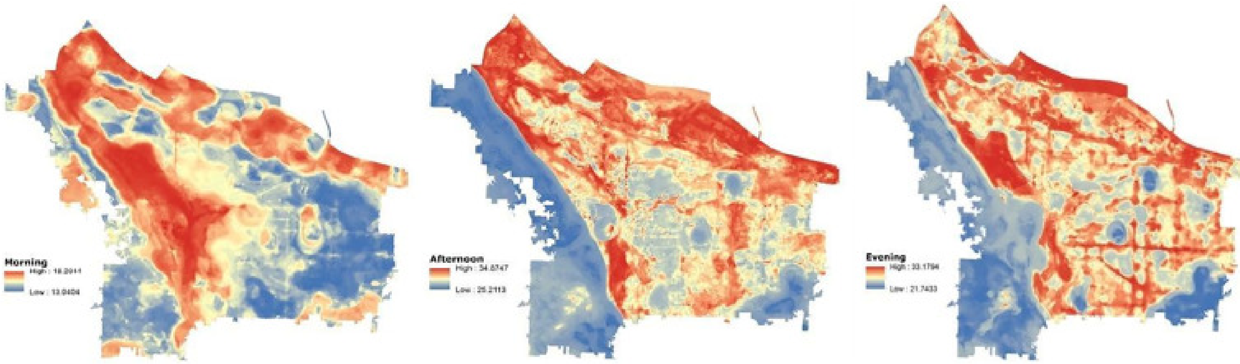

Figure 1. Distribution of air temperature (C°) across Portland, OR, with morning (left), afternoon (middle) and evening (right) distributions of heat (Voelkel and Shandas, 2017).

Data Bins

To understand the relationships between the variables and building energy use, data were binned two ways and analyzed using a variety of statistical methods, which are described below. The first data bin includes homes segmented by temperature, using a spatial approach which divided the data into equal intervals to ensure a similar number of homes in each temperature bin. This resulted in approximately 2,500 observations in 5 temperature designations (Figure 2). The second bin split the data by homes with installed AC (n=6,519), and homes without (n=5,850), resulting in almost two equal groups.

Statistical and Spatial Analyses

Summary statistics are presented for building characteristics and temperature values. To compare between identified groupings, a Welch's two sample t-test was first calculated to understand whether the variance between means in the datasets was statistically significant (West, 2021). Results are reported as significant for $p < 0.05$ and highly significant for $p < 0.001$. Because of the large sample size, we also calculated a Cohen's d to determine the effect size of each variable, which identifies the difference between the two means in units of standard deviation and can be used to better understand practical significance. Results are reported with a 95% confidence level (<0.05), and the effect size includes threshold magnitudes of $d = 0.01$ (negligible), $d = 0.20$ (small), $d = 0.50$ (medium), $d = 0.80$ (large), $d = 1.20$ (very large) and $d = 2.0$ (huge) (Cohen, 1992; Sawilowsky, 2009). The software package R was used calculate Welch's t-tests, Cohen's d, and summary statistics (R Documentation, 2021). For each set of parameters in the groupings, separate t-tests and Cohen's d were calculated for each variable.

Geographic Information System software (ArcGIS-pro) was used to analyze spatial-temporal relationships between building characteristics and temperature in the datasets. Spatial analysis provides location-based perspectives to complex problems, focusing on characteristics and relationships using statistical approaches. Each home was plotted with the associated temperature values joined to each datapoint. For this study, the Moran's I test was used to determine spatial autocorrelation and investigate the urban-scale patterns of AC installations (Anselin, Bera, Florax, & Yoon, 1996). To further identify clusters of installed AC, and to statistically analyze those patterns, an optimized cluster analysis (Getis-Ord Gi*) was used (Ord & Getis, 1995). Both approaches have been used in previous study to study the influence on varying factors on building energy use (Ahn & Sohn, 2019; Cheng, Hsu, Li, & Ma, 2018).

The Getis-Ord Gi^* statistic measures the intensity of clustering of high or low values (i.e., counts of installed AC) in an area relative to its neighbors. The sum for an area and its neighbors is compared proportionally to the sum of all areas. When an area's sum is different than expected, and that difference is too large to be the result of random chance, the Z score is statistically significant. The Getis-Ord Gi^* statistic generates Z scores (standard deviations) and p-values (probabilities) for each area that indicate whether AC presence in an area is statistically clustered compared neighboring areas. A Z score above 1.96 or below −1.96 means that there is a statistically significant hot spot or cold spot of AC presence at a significance level of $P < 0.05$. The larger a bin's Z-score, the more intense the clustering of values (hot spot).

Results

Temperature Analysis

Evening temperature distribution was plotted for each home in the dataset throughout the city with darker points representing warmer temperatures, and lighter colors representing cooler evening temperatures (Figure 2). Five temperature bins were identified, ranging from 24.4°C (76°F) in the coolest parts of the city to 31.9°C (89.6°F) in the warmest, during the evening sampling period. Areas with the most greenspace and tree canopy consistently had the lowest evening ambient temperature.

Figure 2. Distribution of evening temperatures for each home in the dataset. Temperature values range from white, representing cooler evening temperatures to dark red, representing warmer evening temperatures. Ledgend displays temperature value ranges in Celcius.

Ambient evening air temperatures for all homes in the sample ranged from 22.4°C to 31.9°C. Analysis of installed AC within the five temperature bins shows that the amount of installed AC throughout the city is highest in the areas with the coolest evening temperature, with 67% of homes in the coolest bin shown to have AC, compared to a range of 47-51% for all other bins (Figure 3).

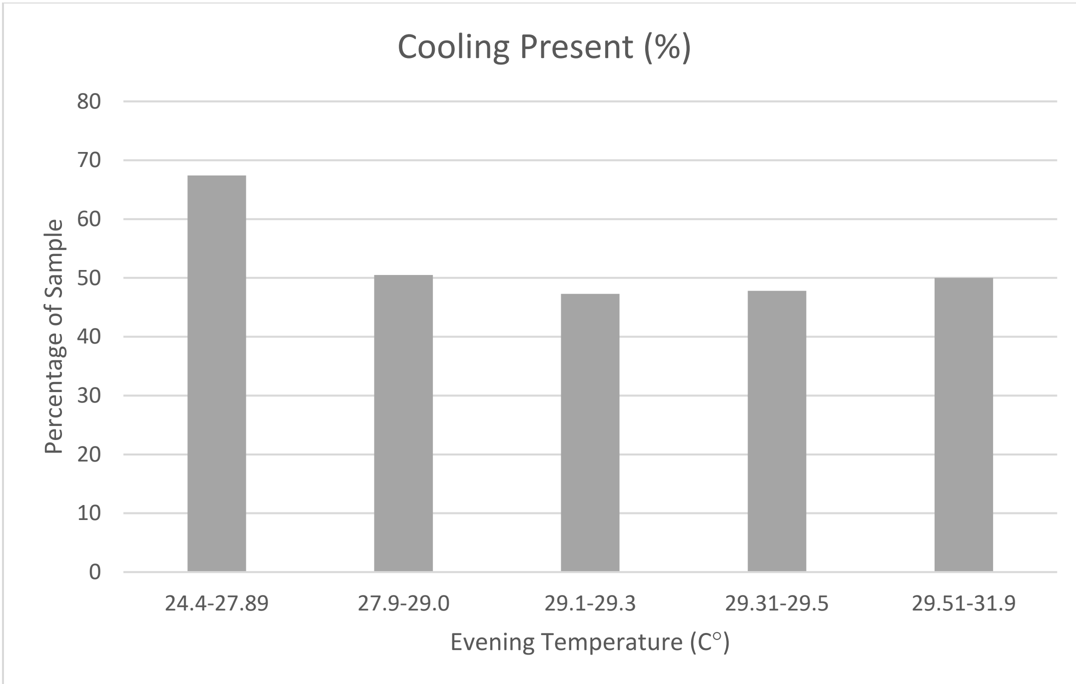

Figure 3. Cooling presence as a function of evening temperature.

Figure 4 presents a box and whisker plot for variables tested in the temperature bins. The green boxes represent homes in the coolest parts of the city where evening air temperatures were measured between 24.4-27.89°C and red boxes present homes in the warmer areas of the city where evening temperatures were measured between 27.9-31.9°C. Boxes show interquartile range with mean values denoted by the black bar in the box and whiskers are limit values representing the 25^{th}-75^{th} percentiles, with outliers presented as circles outside the whiskers. All variables show a practical difference between homes in cooler and warmer areas. The largest differences can be seen in home age, size and base energy use intensity (EUI).

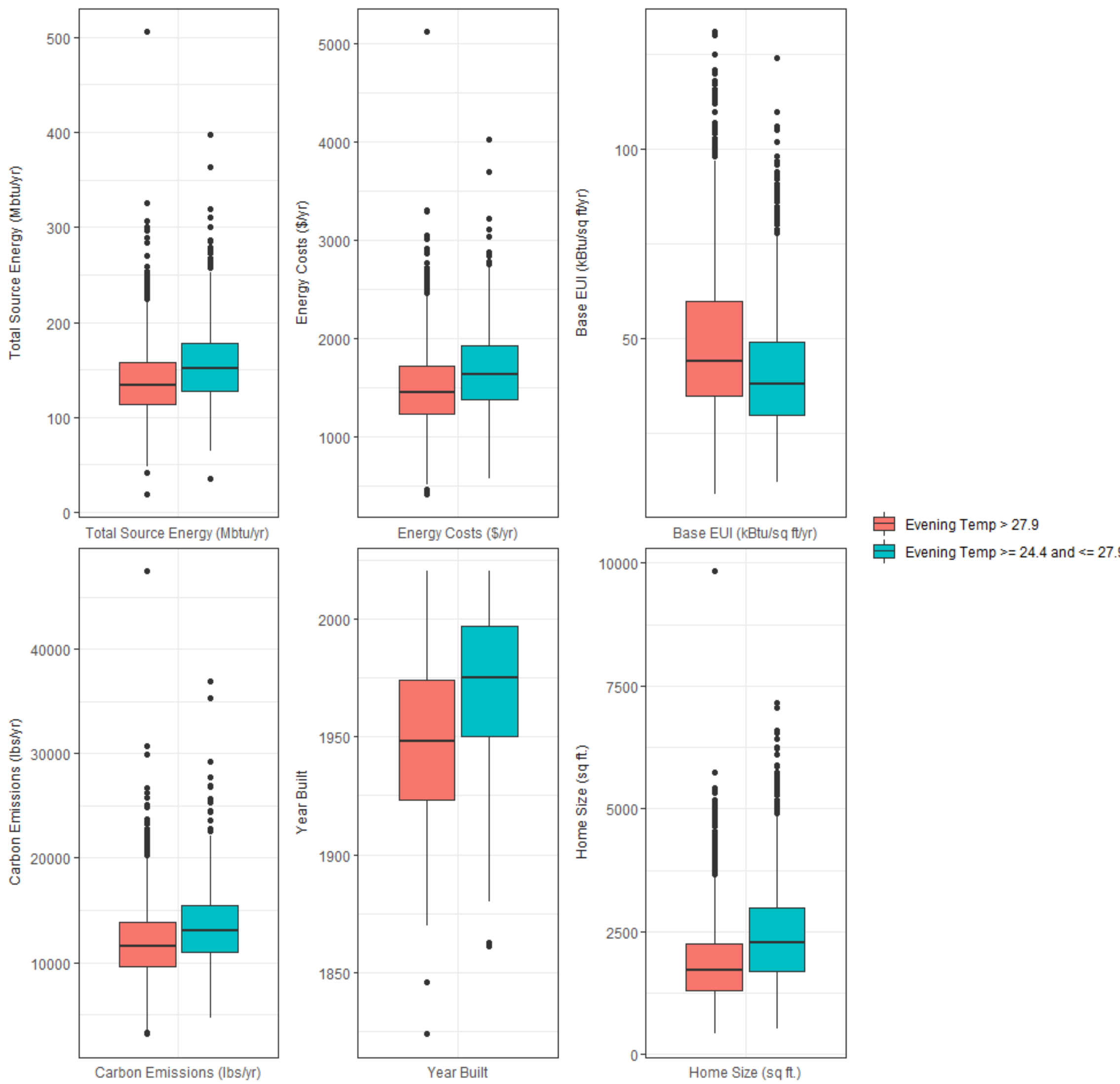

Figure 4. Summary of homes by temperature bins with green showing the coolest parts of the city (24.4-27.89°C) and red the warmest (27.9-31.9°C). Boxes show interquartile range with mean values denoted by the black bar in the box and whiskers are limit values representing the 25th-75th percentiles, with outliers presented as circles outside the whiskers.

Welch's t-test and Cohen's d effect test results are presented in Table 2 illustrating the statistical and practical significance of the variables tested. All variables were statistically significant with p-values <.0001. Effect size estimates using the Cohen's d statistic also showed differences in variables, with the largest variance observed in year built, home size and total source energy use (medium effect), with smaller differences observed in base EUI and energy costs (small effect).

Table 2. Welch's t-test and Cohen's d Estimate for variables binned by ambient evening air temperature.

Parameter	**Welch's t-test**		**Cohen's d Estimate**	
	t	**p-value**	**d estimate**	**Interpretation**
Year Built	27.39	<.0001**	0.56	Medium
Home Size (sq ft)	28.9	<.0001**	0.79	Medium
Base EUI (kBtu/sq ft/yr)	-19.63	<.0001**	-0.39	Small
Total Source Energy (Mbtu/yr)	21.21	<.0001**	0.51	Medium
Energy Costs ($/yr)	19.61	<.0001**	0.45	Small

Air Conditioning Analysis

Homes with installed AC are identified as those with a centrally installed unit. This includes traditional split system or packaged air conditioners, but also heat pumps and mini-split heat pumps. Window and other auxiliary or portable units are not included in the HES database and were not considered in this analysis. In total, 53% of homes in the sample (n=12,369) reported an installed AC system, with both median and mean efficiency values of 13 SEER, which is under the ENERGY STAR threshold of 14.5 SEER. Summary statistics comparing the two groupings (Table 3) shows the largest difference in median values present in year built, home size and EUI.

Table 3. Residential building summary statistics for homes with and without AC

	Homes with AC (n=6,519)			**Homes without AC (n=5,850)**		
Parameter	**Mean**	**Median**	**Range (10-90%)**	**Mean**	**Median**	**Range (10-90%)**
Morning Temperature (ºC)	15.2	15.3	13.2- 17.3	15.3	15.4	13.3- 17.3
Evening Temperature (ºC)	28.7	29.2	24.5- 30.5	29.0	29.5	24.4- 31.9
Afternoon Temperature (ºC)	31.1	31.4	27.2- 33.2	31.3	31.5	26.6- 32.7
Year Built	1964	1961	1915- 2013	1946	1942	1909- 2005
Home Size (sq ft)	2,054	1,908	1,090- 3,185	1,836	1,737	1,000- 2,751
Base EUI (kBtu/sq ft/yr)	44	40	26-71	51	46	30-81
Total Source Energy (Mbtu/yr)	143	139	102-209	138	135	100-182
Energy Costs ($/yr)	1,545	1,505	1,085 – 2,079	1,515	1,460	1,077 – 2,039

Figure 5 presents the differences in the with and without AC groupings, and Table 4 presents results of the corresponding statistical analyses. While all variables were found to be significant in the Welch's t-test, the large sample size makes it easy to find differences in the two groups. Further analysis using the Cohen's d statistic found the effect size of most variables to be negligible, with the largest difference observed in the year built.

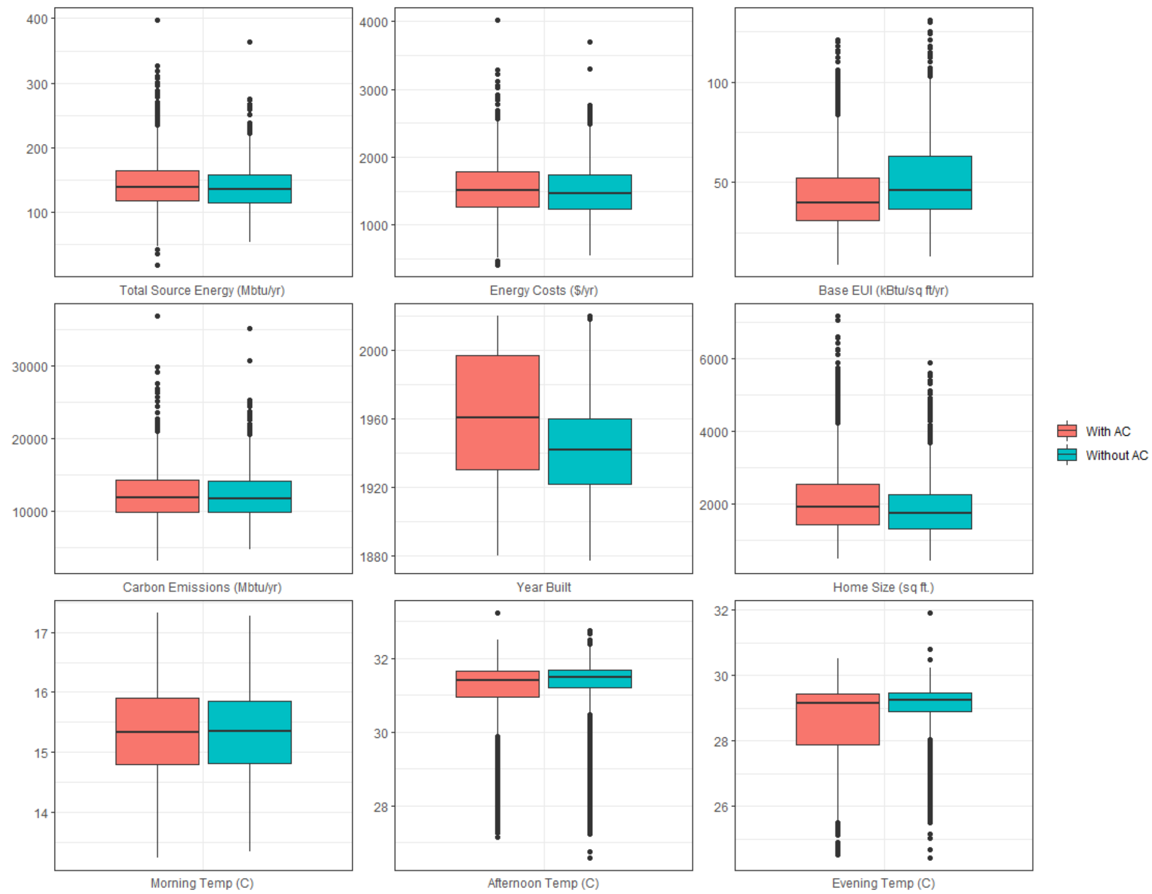

Figure 5. Comparisons of each variable according to the presence of AC. Boxes show interquartile range with mean values denoted by the black bar in the box and whiskers are limit values representing the 25th-75th percentiles, with outliers presented as circles outside the whiskers.

Table 4. Two-sample Welch's t-test and Cohen's d estimate results for homes with and without installed AC

	Welch's t-test		**Cohen's d Estimate**	
Parameter	**t**	**p-value**	**d estimate**	**Interpretation**
Morning Temperature (°C)	1.9996	0.04556*	0.04	Negligible
Evening Temperature (°C)	-15.84	<.0001**	-0.28	Small
Afternoon Temperature (°C)	-14.09	<.0001**	-0.25	Small
Year Built	29.275	<.0001**	0.53	Medium
Home Size (sq ft)	15.321	<.0001**	0.27	Small

Base EUI (kBtu/sq ft/yr)	-20.772	<.0001**	-0.37	Small
Total Source Energy (Mbtu/yr)	7.9279	<.0001**	0.14	Negligible
Energy Costs ($/yr)	4.3057	<.0001**	0.08	Negligible

* Significant at a 95% confidence level
** Significant at a 99% confidence level

Analysis of spatial autocorrelation using the Global Moran's I showed that the presence of air conditioning is not randomized, but clustered throughout the city (z-score 92.8, p-value <0.001) with greater numbers located in higher income areas. Optimized Hot Spot Analysis (Getis-Ord Gi*), identifies statistically significant areas throughout the city that have high and low of AC installations. Additionally, correlation analysis focused specifically on the results of the hot spot analysis did not show a significant correlation value between the presence of air conditioning and building age, indicating that both new and older homes have installed systems in these areas. Figure 4 presents the results of the Getis-Ord Gi* analysis. Red areas indicate statistically significant clusters (hot-spots) of installed AC, blue areas indicate statistically significant clusters (cold-spots) of homes without AC. The data are presented over the evening temperature raster to provide reference to ambient temperature distribution.

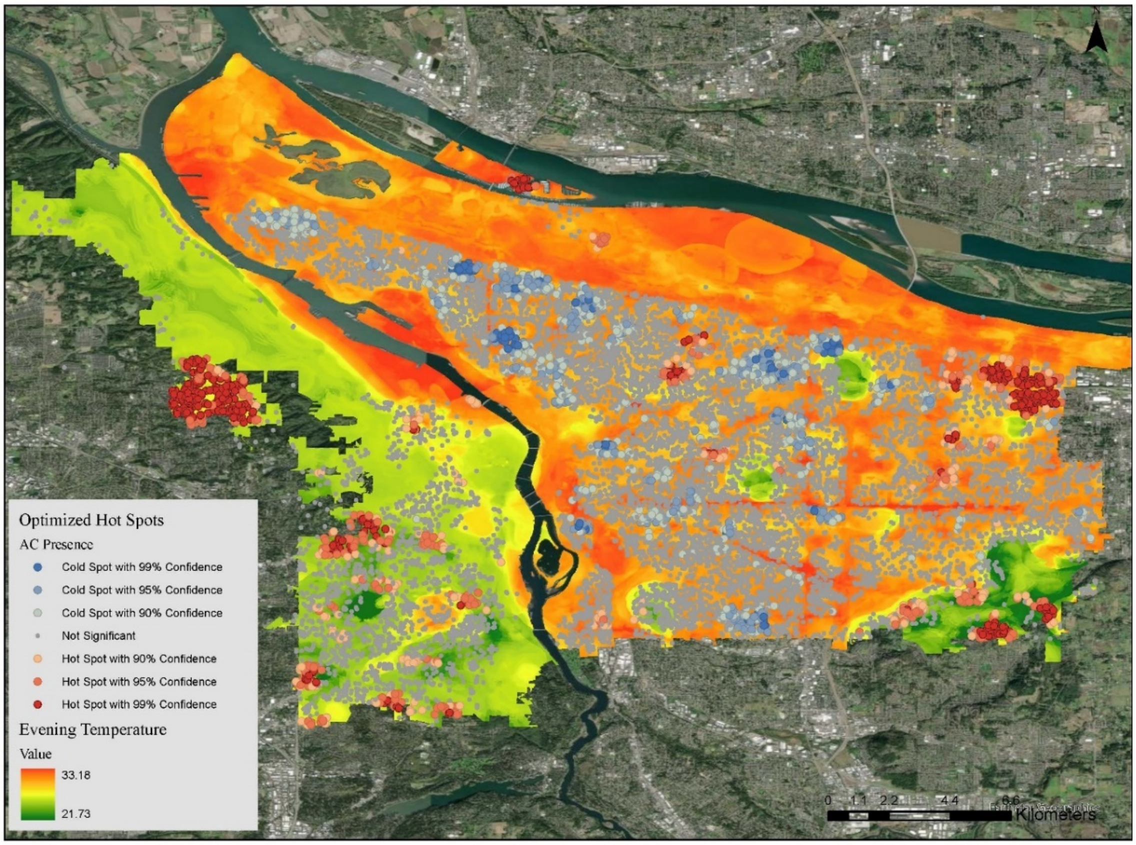

Figure 6. Hot spot analysis (Getis-Ord Gi*) of presence of AC throughout Portland. The analysis is presented overlaid on the evening temperature raster. Areas with high clusters of installed AC are presented in red (p-value >0.001), and areas with clusters of no AC are presented in blue (p-value >0.001). Gray areas are not statistically significant.

Figures 5-7 present results from the Hot Spot analysis at a more granular scale throughout the city.

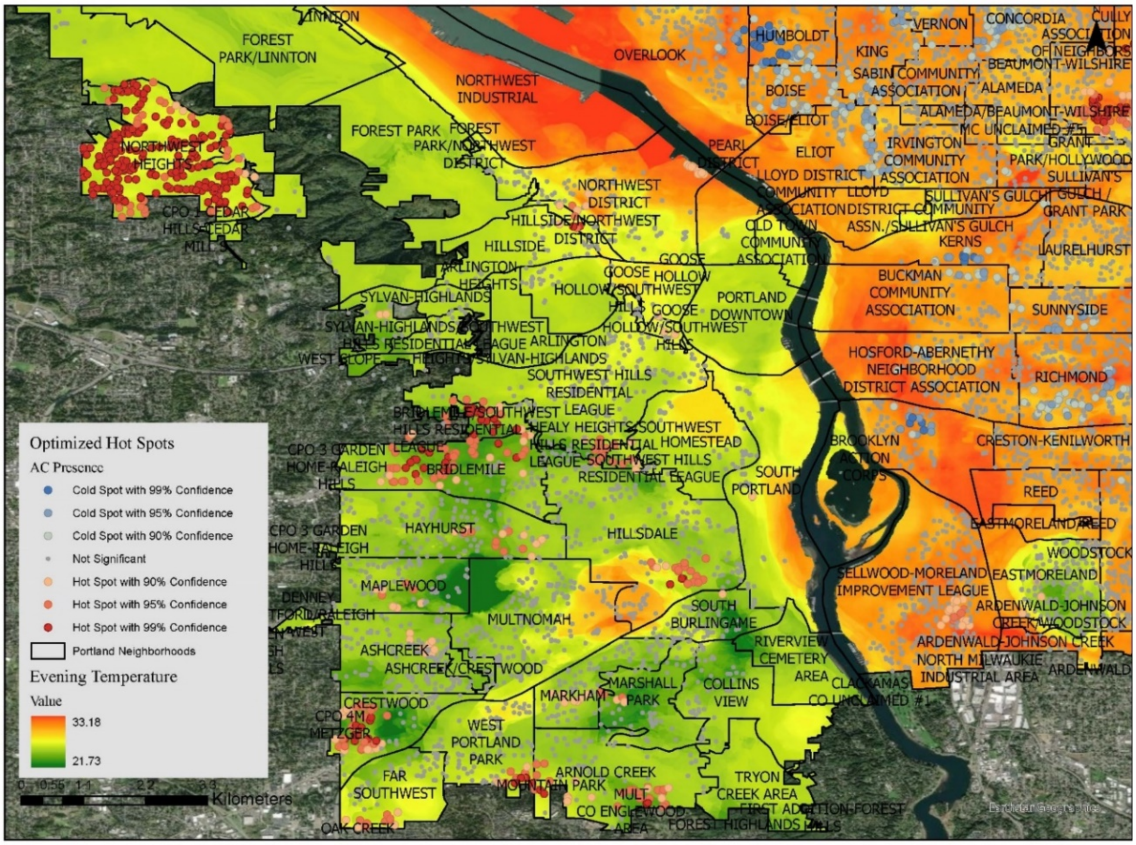

Figure 7. Hot spot analysis (Getis-Ord Gi*) of presence of AC in the Southwest, Northwest and inner-East Portland, OR. The analysis is presented overlaid on the evening temperature raster where orange indicates warmer temperatures and green indicates cooler temperatures. Areas with high clusters of installed AC are presented in red (p-value >0.001), and areas with clusters of no AC are presented in blue (p-value >0.001). Gray areas are not statistically significant.

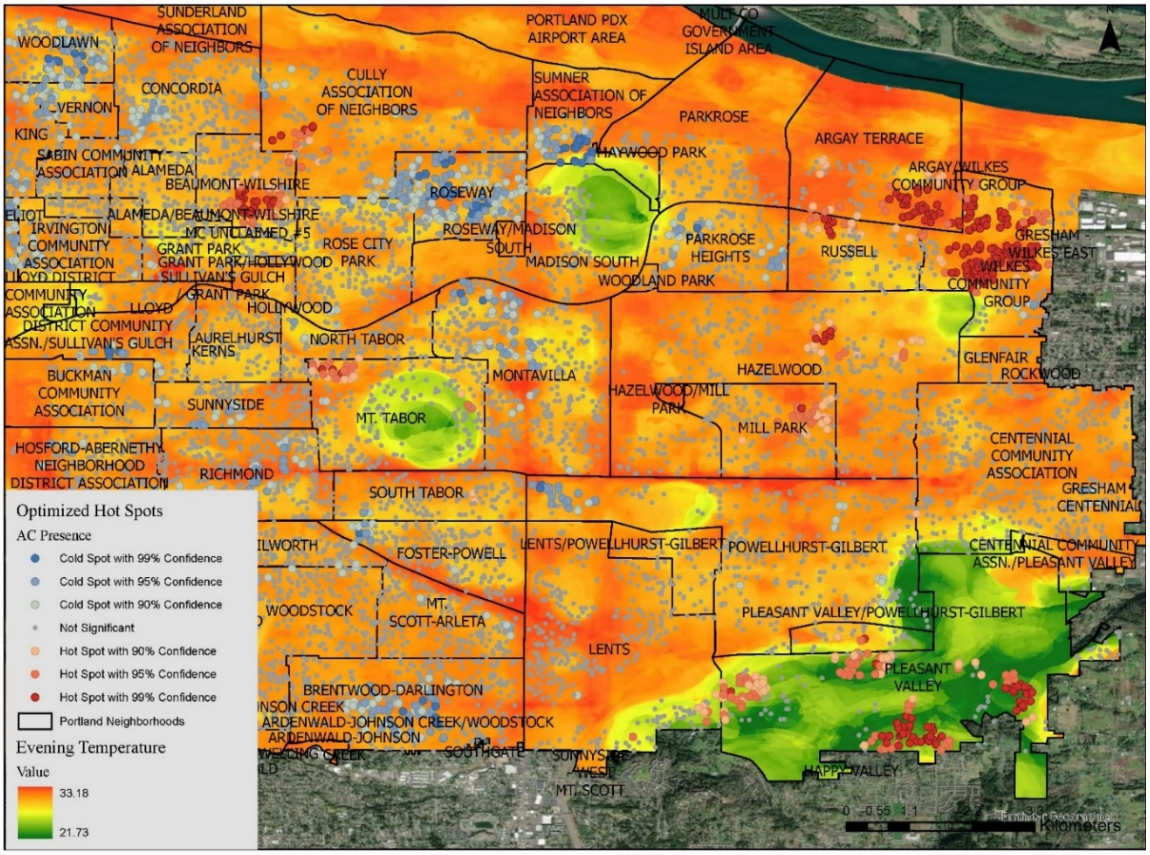

Figure 8. Hot spot analysis (Getis-Ord Gi*) of presence of AC in the Southeast, East and Northeast portion of Portland, OR. The analysis is presented overlaid on the evening temperature raster where orange indicates warmer temperatures and green indicates cooler temperatures. Areas with high clusters of installed AC are presented in red (p-value >0.001), and areas with clusters of no AC are presented in blue (p-value >0.001). Gray areas are not statistically significant.

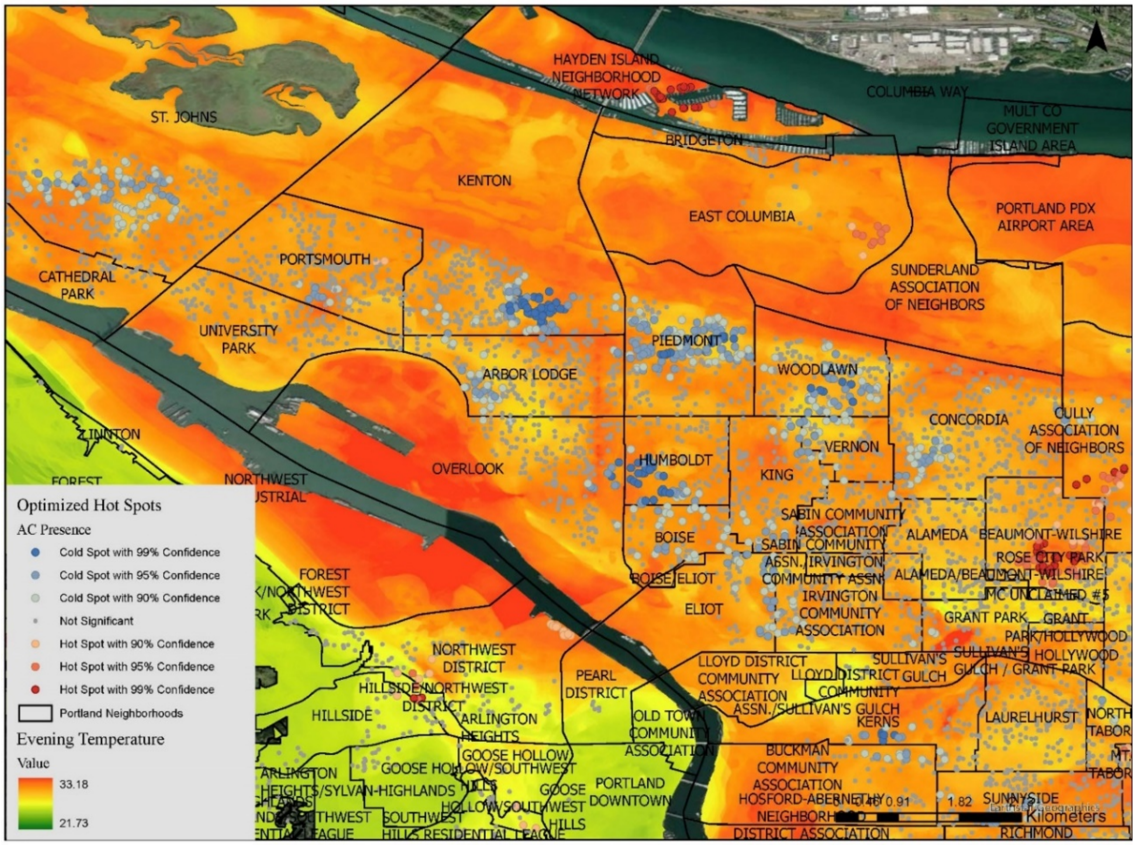

Figure 9. Hot spot analysis (Getis-Ord Gi*) of presence of AC in the Downtown, North and Northeast portion of Portland, OR. The analysis is presented overlaid on the evening temperature raster where orange indicates warmer temperatures and green indicates cooler temperatures. Areas with high clusters of installed AC are presented in red (p-value >0.001), and areas with clusters of no AC are presented in blue (p-value >0.001). Gray areas are not statistically significant.

Case Studies

To assess results on a more granular scale, a case study of one of the coolest neighborhoods (Forest Heights) and one of the hottest neighborhoods (Piedmont) were identified to compare.

<u>Forest Heights</u>

The Forest Heights neighborhood is located adjacent to Portland's Forest Park in Northwest Portland. The site was purchased in the 1970's and developed in the 1980's as a subdivision of luxury homes, and is still partially managed by a homeowner's association, which manages 215 acres of common area within the neighborhood[1],[2]. The neighborhood consists of large single-family homes, with a median household income of $165,976 (U.S. Census Bureau, 2020). The area is not dense, with large homes built generally between 1973-2001. The mean evening temperature in the neighborhood is 27.9°C (82°F), one of the coolest areas in the city during heat waves and extreme heat. Figure 8 Presents an aerial image of the neighborhood boundary and a closer view of a residential street.

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[1] Forest Heights Homeowners Association. https://www.fhhoa.com/page/40965~845859/history-of-forest-heights

[2] Oregon Historical Society. http://librarycatalog.ohs.org/O90000/OPAC/Details/Record.aspx?BibCode=21060992

Figure 10. Areal image of Forest Heights neighborhood in Northwest Portland, and snapshot of housing size and density. Images from Google Maps.

Homes in this area have a statistically significant amount of installed AC, even though neighborhood is located in a part of the city with some of the coolest temperatures (Figure 9). This indicates that regardless of need, homes in this area run AC for thermal comfort.

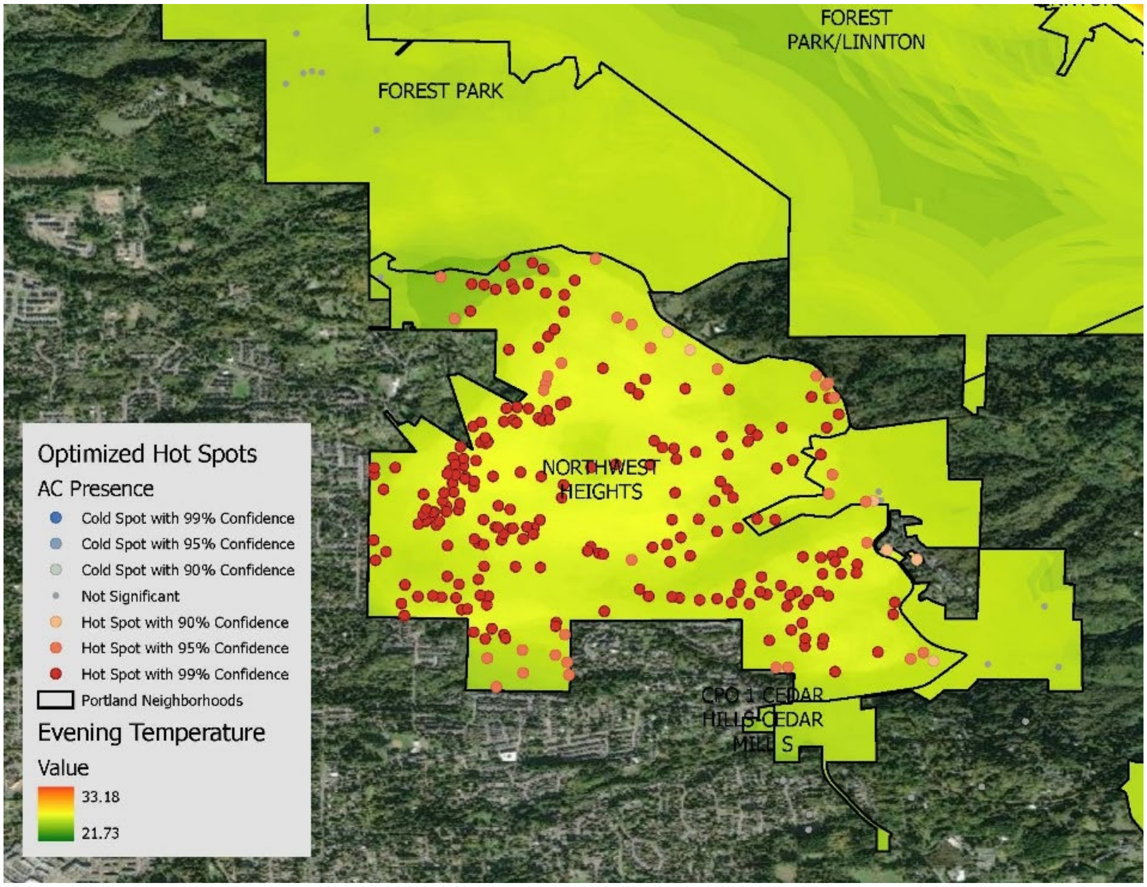

Figure 11. Hot spot analysis (Getis-Ord Gi*) of presence of AC in Forest Heights neighborhood. The analysis is presented overlaid on the evening temperature raster where orange indicates warmer temperatures and green indicates cooler temperatures. This area has some of the highest clusters of installed AC are presented in red (p-value >0.001).

Figure 10 presents a typical urban form in the Forest Heights neighborhood, which is dominated by single-family homes on large lots with dense tree canopy. The influence of the urban form keeps ambient temperatures cooler in this area compared to other areas throughout the city.

Figure 12. Typical residential street in Forest Heights. Images from Google Maps.

Piedmont

The Piedmont neighborhood was originally platted in 1889 and developed to be a middle-class residential suburb of Portland (Dixon et al., 1990). Piedmont is a dense, gentrifying, inner-city neighborhood bordered by Interstate 5 to the west, and the Columbia Slough to the North with a median household income of $62,321 in 2020 (U.S. Census Bureau 2020). The area includes single family, multifamily, commercial and industrial buildings, with smaller homes built anywhere from 1890 to present day. The urban form of the neighborhood is denser than Forest Heights, with larger industrial areas, concrete and roads. The mean evening temperature in the neighborhood is 29.8°C (86°F), one of the warmer areas in the city during heat waves and extreme heat. Figure 11 Presents an aerial image of the neighborhood boundary and a closer view of a residential street.

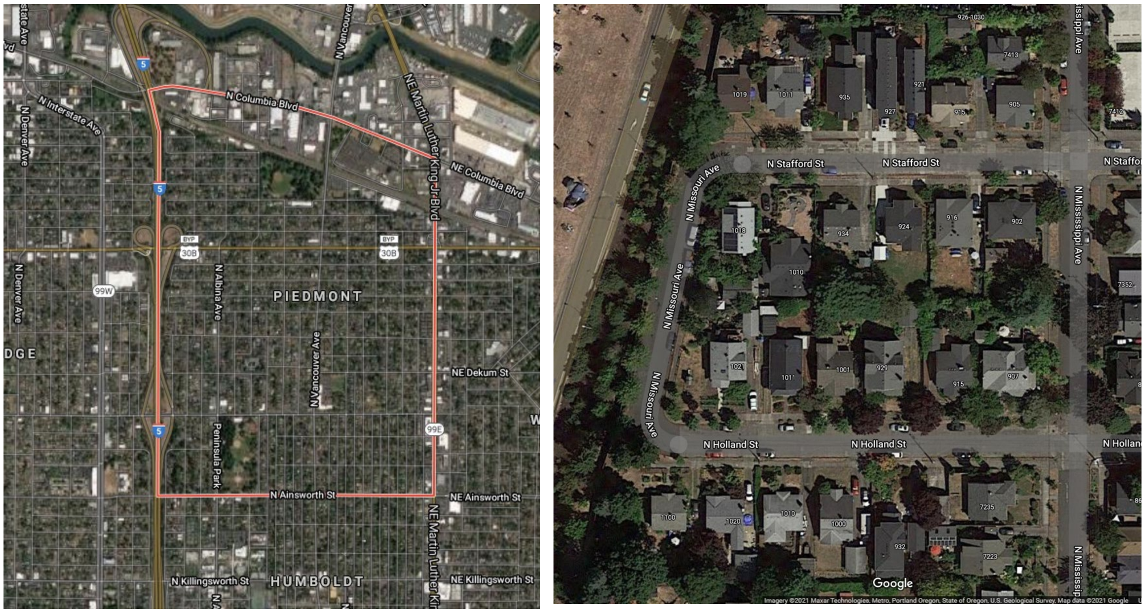

Figure 13. Areal image of Piedmont neighborhood in North Portland, and snapshot of housing size and density. Images from Google Maps.

Homes in this area have low levels of installed AC, even though neighborhood is located in a part of the city with some of the hottest temperatures (Figure 12). Homes in this area are also more energy intense, as indicated by the EUI metric. This means that the use of energy per square foot of space is high, even though occupants have less access to in-home cooling.

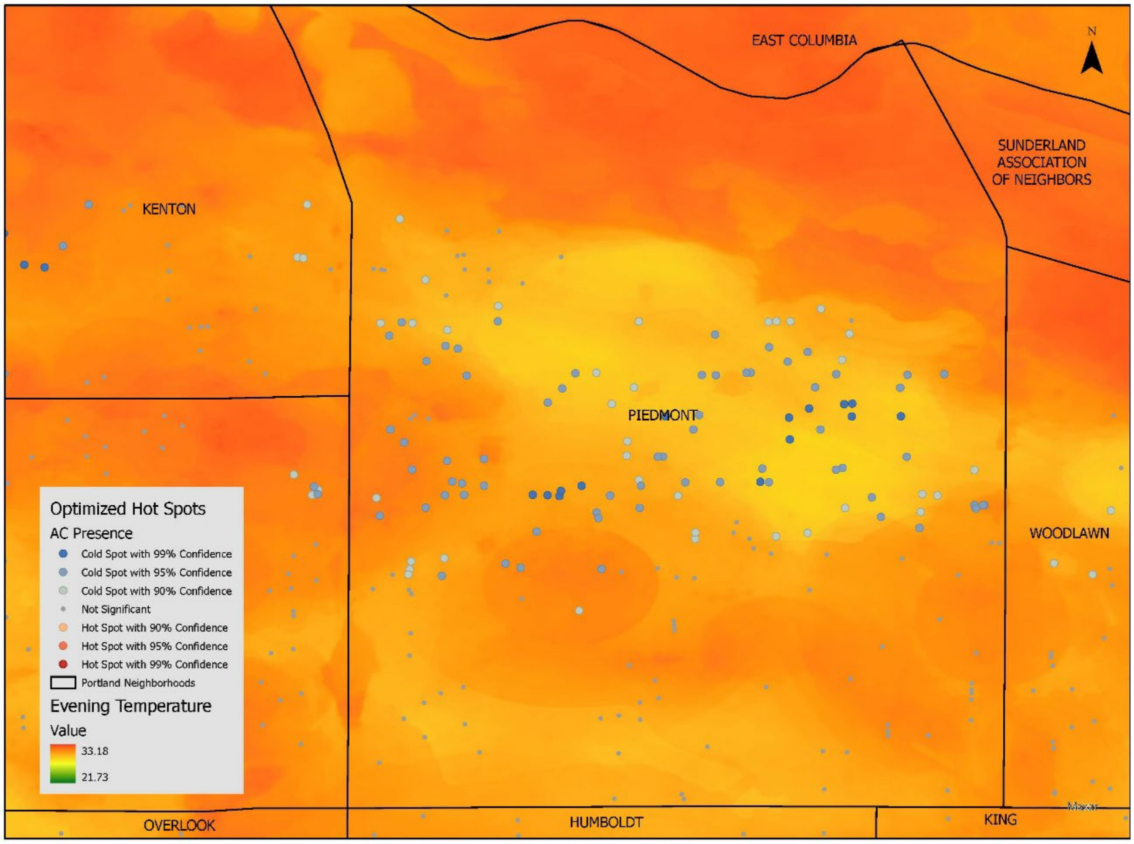

Figure 14. Hot spot analysis (Getis-Ord Gi*) of presence of AC in the Piedmont neighborhood. The analysis is presented overlaid on the evening temperature raster where orange indicates warmer temperatures and green indicates cooler temperatures. This area has some of the lowest amounts of installed AC are presented in blue (p-value >0.001).

Figure 13 presents a typical urban form in the Piedmont neighborhood, which includes single-family, multifamily, commercial, and industrial areas. There is less tree canopy than in Forest Heights, and more asphalt. The influence of the urban form keeps ambient temperatures hotter in this area during heat waves and periods of extreme heat.

Figure 15. Typical residential street in Piedmont. Images from Google Maps.

Discussion

In Portland, a growing number of homes have installed central AC systems (53%, n=12,369). The distribution of AC throughout the city is clustered (Moran's I: z-score 92.8, p-value <0.001), with the highest rates of installed AC observed in the coolest areas of the city. Previous analysis of AC adoption indicates that household income is a determinant of whether AC is present in a home (Davis & Gertler, 2015; Goldsworthy & Poruschi, 2019; Ramos et al., 2021). The analysis that binned homes by temperature shows that year built (d = 0.56), home size (d = 0.79) and total source energy consumption (d = 0.51) to have a medium effect size and base EUI (d = -0.39) and energy costs (d = 0.45) to have small effect size. This finding indicates that homes located in the coolest areas in the city are newer, larger and use more total source energy consumption. Previous analysis indicates that age and size has traditionally been an indicator of energy use (Aksoezen, Daniel, Hassler, & Kohler, 2015; Frederiks et al., 2015). This analysis suggests that ambient temperature may also be an indicator of building energy use. The small effect size of EUI and energy costs points to these variables being less impactful.

Additionally, the highest statistically significant clusters of installed AC using spatial analysis were observed in the coolest areas throughout the city, indicating that these areas run AC systems, even though their ambient temperatures are lower than other areas. The lowest clusters of homes without AC are concentrated in the inner-city and include many traditionally low-income neighborhoods which also have less greenspace and higher ambient temperatures, highlighting the vulnerability of residents in these areas. Urban heat mitigation strategies should fucus on these neighborhoods, due to heightened exposure risk of residents. When AC systems are present, the mean and median SEER ratings in the sample throughout the city was only 13, highlighting significant inefficiency in mechanical systems, regardless of the neighborhood's overall MHI.

There is a fundamental, systemic issue associated with the inefficient housing stock, especially for populations experiencing energy insecurity. In this study, this observation is highlighted by high EUI in homes located in heat islands, without AC. These homes are older, have less insulation, inefficient windows, and higher air infiltration. Although these homes use less energy in total and trend lower in emissions, higher EUI is an indicator of increased energy poverty risk (Jessel, Sawyer, & Hernández, 2019; Reames, 2016b). The added risk presents further complexities when considering climate change mitigation strategies. For example, when considering interventions for extreme heat in low-income areas with high EUI, the building envelope should be tightened before adding mechanical equipment such as central AC, heat pumps or mini-split heat pumps to reduce the risk of increasing energy burdens. When the building envelopes are tightened, adequate ventilation systems must also be installed to ensure indoor air quality is not degraded (Singer, Chan, Kim, Offermann, & Walker, 2020). These comprehensive measures point to the need for deep energy retrofits in homes, which often present barriers for occupants or programs due to cost (Streicher, Mennel, Chambers, Parra, & Patel, 2020). However, the need for an extremely energy efficient, advanced building stock is critical, both to decrease primary energy use and to provide climate change resilience. For the most vulnerable populations, there must be programs to support deep energy retrofits without increasing energy poverty.

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Chapter 3. Experimental Assessment of Interventions to Reduce $PM_{2.5}$ in a Residence During a Wildfire Event

Introduction

Recent decades have been marked by increased concern about our indoor environments related to the quality of indoor air and pollutant exposure. The average American spends 90% of their day indoors, where exposure to pollutants can be higher than outdoors (US EPA, 2018). The lack of regulation of pollutant concentrations in the indoor environment means that occupants may be subject to significant exposure risks without being aware of it. The health consequences are not trivial; there is robust literature that has found direct linkages between indoor pollutant exposure and health, including ailments such as general irritation, headaches, dizziness, fatigue, respiratory diseases, heart disease, cancer and premature death (Dales et al., 2008; Jones, 1999; Kaden, Mandin, Neilsen, & Wolkoff, 2010; Sundell, 2004; Tham, 2016; US EPA, 2018; Wolkoff, 2018). These observations have been made without considering factors that would cause pollutant concentrations to increase, such as we see with wildfire smoke. Nazaroff (2013) noted that climate change will increase the need for ventilation, filtration and air cleaning as a result of degraded IAQ due to elevated indoor pollutant concentrations.

Wildfire trends throughout the world continue to increase. Climate change is a major culprit, increasing the potential for wildfires, especially large-scale, megafires (Barbero et al., 2015; Yongqiang Liu et al., 2010). In the Pacific Northwest, climate change is increasing outdoor particulate matter concentrations through extreme heat and wildfire events (Geiser & Neitlich, 2007). During wildfire events large amounts of woodsmoke is released that along with fine and ultra-fine particulate matter ($PM_{2.5}$), contain complex gaseous compounds that include nitrogen oxides, carbon monoxide, methane and hundreds of volatile organic compounds (VOCs) and oxygenated VOCs (OVOCs) (Jaffe et al., 2020). Prior studies have found that exposures to wildfire smoke increase mortality risk, respiratory illness, and cardiovascular mortality (Aguilera, Corringham, Gershunov, & Benmarhnia, 2021; Anjali et al., 2019; Johnston et al., 2011; Richardson et al., 2012). Like with other types of pollutant exposures, vulnerable populations such as children and the elderly have higher risks for illness (Holm, Miller, & Balmes, 2021).

A recent case study in Washington state found that $PM_{2.5}$ levels increased significantly indoors during a wildfire event (Kirk et al., 2018). Another recent study in Australia found that remaining indoors during wildfire events does protect occupants from exposure, but the level of protection is highly variable and dependent on housing characteristics and ventilation (Reisen et al., 2019). Furthermore, tightening envelopes to reduce infiltration requires proper ventilation strategies in order to ensure pollutants from inside do not increase over time (Rajagopalan & Goodman, 2021). In one study, properly sized air cleaners were shown to decrease $PM_{2.5}$ by as much as 63-88% compared to homes without (Henderson et al., 2005). In a California study using low-cost Purple Air sensors, mean $PM_{2.5}$ indoor/outdoor ratios decreased during fire events compared to non-fire events (Liang et al., 2021).

Public health officials encourage residents to keep windows closed and use portable air cleaners during high smoke days to offset impacts of smoke inhalation (Barn et al. 2016; Henderson, Milford, and Miller 2005). One study looked at potential impacts of wildfire interventions that included combinations of forced air system operation, filtration and air cleaners on health, finding that interventions could decrease both hospital admissions and deaths attributed to wildfire smoke (Fisk & Chan, 2017). This study aims to evaluate the mass balance exposure portion of the Fisk & Chan (2017) model, using experimental data gathered during a large wildfire event in Portland, OR during 2020. This event brought record-breaking air quality issues, with the air quality index (AQI) reaching higher than 500 (>500.4 ug/m^3), which is the highest level captured by the AQI system (U.S. EPA, 2018).

Using experimental data and modeling approaches, we ask the following research questions: 1) what are the measured $PM_{2.5}$ concentrations inside a home during a large fire event, and what is the ratio of indoor/outdoor (I/O) levels? 2) How do interventions such as high-efficiency filtration and portable air cleaners impact indoor $PM_{2.5}$ concentrations? 3) How does the measured performance perform relative to modeled performance from previous study?

Methods

There are two primary activities associated with this study. The first is the instrumentation and physical data collection during the wildfire event between September 12 – 19, 2020. The second is the modeling activity. Both are discussed in detail below.

Building Instrumentation and Pollutant Data Collection

Building Characteristics

One home, built in 1928 was instrumented with indoor and outdoor pollutant measurement equipment during the study period of September 12 – 19, 2020. The house is located in inner Northeast Portland, OR and is approximately 2,600 ft2 with includes two stories and a partially finished basement, translating to approximately 16,120 cubic feet of total volume. The home is equipped with a heating, ventilation and air conditioning (HVAC) system that includes a central gas furnace and packaged air conditioner and has exhaust-only ventilation. The central gas furnace is 92 AFUE, and the air conditioner is a 3-ton 13 SEER outdoor packaged unit. There is a high-efficiency capture filter (MERV 13) in the furnace air handler. Additionally, a portable air cleaner with a HEPA filter (with a MERV 16 filter) and an output of 160 CFM was used in the room that was equipped with the particle measurement equipment. Equipment specifications were obtained and included in the model development.

Air Leakage, Envelope Infiltration and HVAC Operation

Air leakage in the building envelope was measured using a TEC Minneapolis Blower Door System and DG-700 digital manometer. The CFM50 value during depressurization and pressurization were averaged and used to calculate the air changes per hour at 50 pascals pressure differential (ACH50), which is the most common method for assessing envelope air leakage in existing residential buildings. It is important to note that the ACH50 value is not intended to indicate a total air exchange rate at normal indoor-outdoor pressures, a value that would require more measurement and modeling. The ACH50 value was translated to a simplified annual averaged infiltration rate using the Lawrence Berkeley National Laboratory infiltration model (Sherman, 1987).

Figure 1. Blower door test set-up for envelope air tightness measurements.

HVAC operation was monitored using airflow anemometers at HVAC registers throughout the house. HVAC duty/state operation was monitored as an airflow rate in m^3/min, measured using an anemometer attached to the registers. to determine when the

HVAC system was operational. Register size was captured and duct diameter was included in airflow measurements.

Air Quality Measurements

Measurements were taken in two primary locations; an outdoor station set up in a backyard and an indoor station set up in the dining room. Figure 2 shows the outdoor and indoor stations and Table 1 provides an overview of air quality measurements and equipment specifications used in the test home.

Figure 2. Equipment setup in the outdoor (right) and indoor (left) areas during the experimental period.

Table 1. Measured air quality parameters

Measurement Device	**Parameters**	**Accuracy[a]**	**Res.**	**Sampling Locations**
Met One ES-642 Photometer	$PM_{2.5}$	±5% traceable standard with 0.6 µm PSL	1 min	Outdoor
Met One BT-645 Photometer	$PM_{2.5}$	±5% traceable standard with 0.6 µm PSL	1 min	Indoor: Central
Onset HOBO UX100-011 Onset HOBO U23 Pro v2	T, RH	±0.21 °C from 0 to 50 °C ±2.5% from 10% to 90%; up to ±3.5% at 25 °C including hysteresis	1 min	Indoor: central (UX100-011); Outdoor (U23)
Clarity Node	NO_2, CO_2, $PM_{2.5}$	0-450 ug/m^3 for $PM_{2.5}$	2 min	Outdoor, Indoor: central

(a) Based on manufacturer specifications.

Modeling Methods

We used a simplified version of the air quality model developed by Fisk and Chan (2017). This model used several codes to describe baseline operation of the home, and then interventions that would improve the air quality during a wildfire event. A summary of the scenarios we tested is shown in Table 2 in bold, where we have a modification of intervention 3 and 4 to include the case for a high efficiency filter with a continuously operated air cleaner. The baseline and intervention 4 are shown for reference but were not included in the model for this study.

Table 2. Summary of the intervention conditions. The intervention codes align with those defined by Fisk & Chan (2017). Intervention i3.5 is a combination of i3 and i4, with the portable air cleaner in operation.

Baseline or Intervention Code*	**Reference Condition**	**Forced Air System Operation**	**Efficiency of Filter in Forced Air System**	**Continuously operating portable air cleaner?**	**Experiment Timeframe**
B1	*NA*	*Intermittent*	*Typical Low*	*No*	-

i3	***B1***	***Intermittent***	***Upgraded to High***	***No***	***9/12-9/16***
i3.5	***B1***	***Intermittent***	***Upgraded to High***	***Yes***	***9/16-9/18***
i4	B1	Continuous	Typical Low	Yes	-

To characterize the types of particle removal, parameterizations employed in modeling of removal processes ($\backslash lambda$) are normalized by the indoor air volume (V) and have units of 1/h. Most of the removal rates are determined experimentally or based on the rating of air filters as shown in Table 2. The rate of removal by the home air conditioning system (λ_F) is calculated based on the air flow rate of the forced air blower (Q) normalized by air volume [1/h], the duty cycle (D), and the filter efficiency (ε).

$$\lambda_F = Q \cdot D \cdot \varepsilon \tag{1}$$

For each intervention, the filter efficiency for the air blower (ε_H or ε_L) and the portable air cleaner are estimated (ε_P). The values used for each parameter are shown in Table 2.

$$\lambda_3 = Q \cdot D \cdot \varepsilon_H \tag{2}$$

$$\lambda_{3.5} = Q \cdot D \cdot \varepsilon_H + Q_P \cdot \varepsilon_P \tag{3}$$

$$\lambda_4 = Q \cdot D \cdot \varepsilon_l + Q_P \cdot \varepsilon_P \tag{4}$$

Once the removal rates are known, the concentration (C) for each baseline is determined based on the outside air concentration (C_o), the particle penetration factor (P) and other parameters from Table 2.

$$K_{B1} = P \cdot \lambda_V / (\lambda_V + \lambda_D + \lambda_F) \tag{5}$$

$$C_{B1} = K_{B1} \cdot C_o \tag{6}$$

In a similar way, the concentrations for other interventions are calculated, based on the intervention number (N), as λ_N for N=3, 3.5, 4, etc.

$$K_N = P \cdot \lambda_V / (\lambda_V + \lambda_D + \lambda_N) \tag{7}$$

$$C_N = K_N \cdot C_o \tag{8}$$

A summary of model parameters is presented in Table 3. The assumptions used by Fisk and Chan are noted, along with the updated metrics gathered through measurement or equipment specifications from the test home. In some cases, the current modeling effort employs the original assumptions used by Fisk and Chan. For equipment specifications, such as MERV rating, the manufacturer specifications were referenced.

Table 3. Assumptions and parameters used as inputs to the model. Items marked with a * were measured in the test home experiment, or ** looked up from equipment specifications.

Parameter	Units	Description	Fisk Mean Values	Test Home
λ_V	1/h	Ventilation rate	0.60	0.71* Calculated from blower door ACH50 rate
λ_D	1/h	Rate of particle removal by deposition on surfaces	0.39	0.39 (Fisk & Chan, 2017)
P	-	Particle penetration factor	0.97	0.97 (Fisk & Chan, 2017)
Q	1/h	Air flow rate of the HVAC normalized by volume	4.36	4.96**
D	-	Duty cycle	0.18	0.28* Experiment Time Series Calculation
ε_L	-	Filter efficiency for $PM_{2.5}$	0.12	-
ε_H	-	Filter efficiency for $PM_{2.5}$	0.27	0.50** Determined from MERV rating using methods from Fisk and Chan
$\varepsilon_p \cdot Q_P$	1/h	Filter efficiency for PM2.5 multiplied by the air flow rate of the portable air cleaner normalized by volume	1	$(0.9 \cdot 0.596)=0.536$** Determined from manufacturer specifications for portable air cleaner
Co	$\mu g/m^3$	Outside particle concentration	56.9	Experiment Time Series Measurement as shown in Figure 4
V	m^3	Volume of the house	404	456.47*

Results

Experimental Results

The blower door results included values of 2,560 CFM50 pressurized and 2,150 CFM50 depressurized. We derived the average of 2,355 for CFM50 total. The average was divided by the measured volume of the home to calculate a final value of 9 ACH50, indicating a moderately leaky envelope. Base leakage infiltration ratio per the LBNL model for Portland OR was determined to be 22. Correction factors derived from (Sherman, 1987) included a height correction factor (0.8), shielding correction factor (1), and leakiness correction factor (0.7). The product of the correction factors informs N, which was determined to be 12.32. The final infiltration rate is ACH50/N, which is equal to 0.71, as presented in Table 3.

The duty cycle for the HVAC system was calculated from the velocity measurements at an air supply duct in the living room using an anemometer. Flow rates higher than 1 m^3/min were considered operation, as shown in Figure 3.

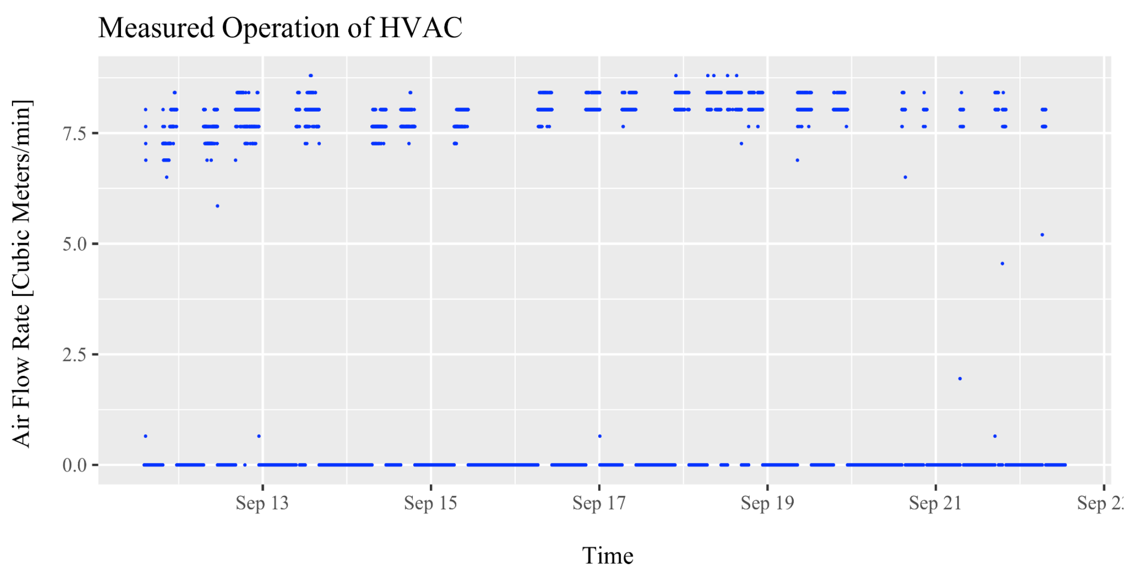

Figure 3. HVAC duty cycle measurements in main living space using an anemometer. Airflow rates higher than 1 m^3/min. were considered in operation.

The outdoor and indoor $PM_{2.5}$ concentrations were measured using a Clarity Node monitor from September 12-19, 2020. Concentrations throughout the study period were extremely high, with peak outdoor concentrations during this period reaching 717 ug/m^3 on September 13th, with a mean value of 277 ug/m^3 and a median value of 282 ug/m^3. The maximum indoor concentration reached 421 ug/m^3 also on September 13th with a mean value of 124 ug/m^3 and a median value of 110 ug/m^3 during the study period. In general, the interior concentrations were much lower than the exterior during the time frame studied but followed a similar trend as the outside air. The AQI reference levels for $PM_{2.5}$ concentrations according to the EPA are unhealthy (AQI 151-200): 65.5-150.4 ug/m^3, very unhealthy (AQI 201-300): 150.5-250.4 ug/m^3, and hazardous (301-500): 250.5-500.4 ug/m^3. Anything over AQI 500 (500.4 ug/m^3) is too high to be captured within the documented index (U.S. EPA, 2018).

Figure 4 presents the raw $PM_{2.5}$ concentrations measured outside and inside the home during the test time frame. The vertical line represents the time when the air cleaner was operating in the home, which was turned on September 16th.

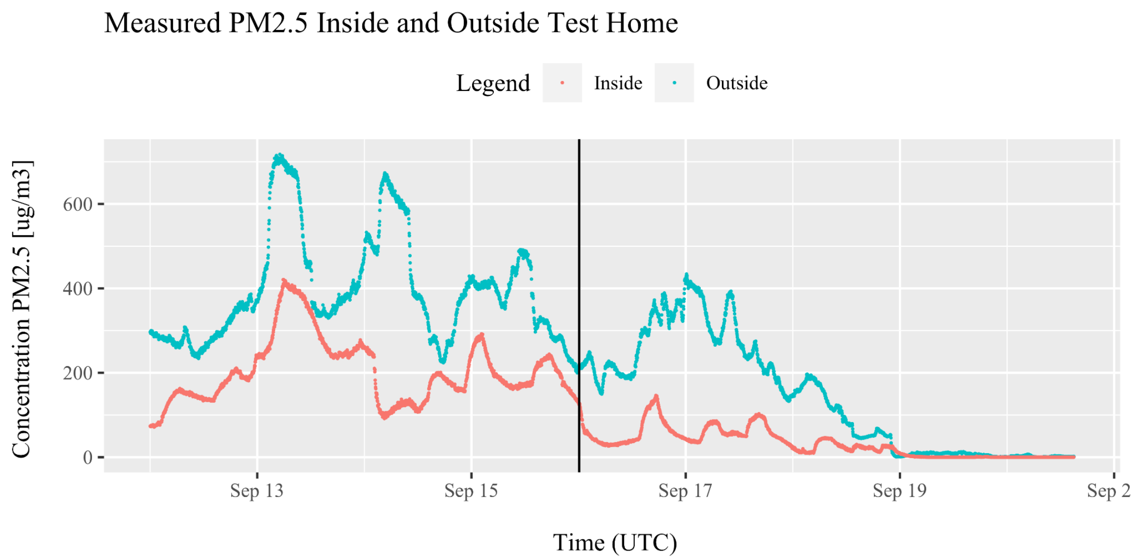

Figure 4. Raw $PM_{2.5}$ concentrations measured with the Clarity Node outdoors (blue) and indoors (red). Black vertical line indicates the time when the portable air cleaner was turned on.

Figure 5 presents the indoor/outdoor (I/O) ratio of $PM_{2.5}$ concentrations during the study period. During the days with the highest $PM_{2.5}$ concentrations, the indoor-outdoor ratio reached almost 0.8, indicating significant penetration of $PM_{2.5}$ from outdoors inside. Before the air cleaner was turned on, there was a significant drop in concentrations indoors because the occupants left the home for a day and the house was left closed. The black vertical line indicates when the portable air cleaner was turned on.

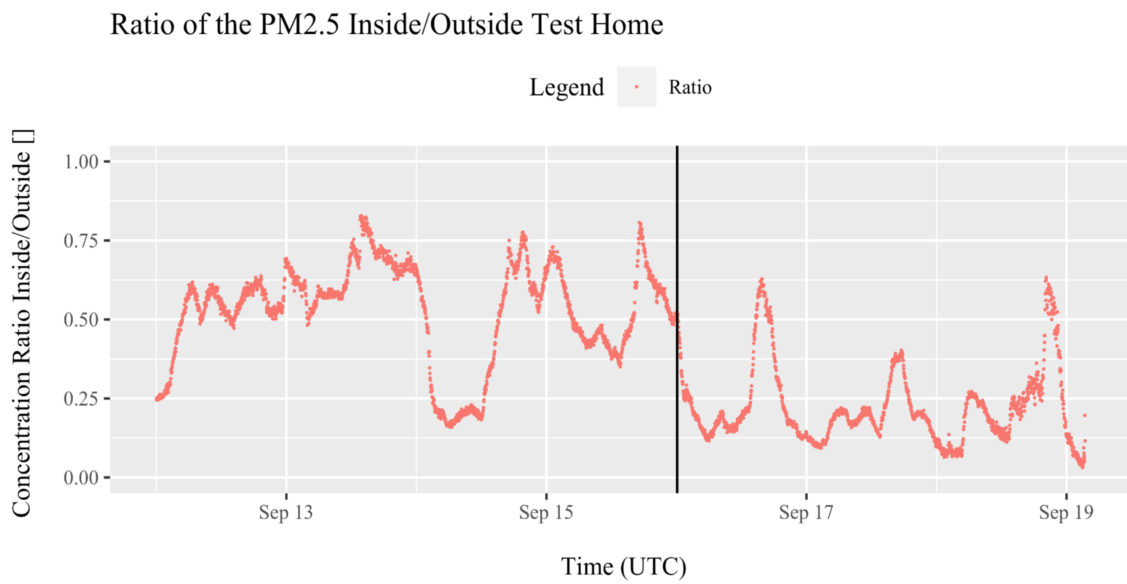

Figure 5. Ratio of outdoor and indoor concentrations of $PM_{2.5}$ measured with the Clarity Node monitor. Black vertical line indicates the time when the portable air cleaner was turned on. The air cleaner remained on from September 16th to the end of the experiment.

Modeling Results

The model was tested first using the published mean values from Fisk and Chan (2017) as shown in Table 4 in the second column. If we test the model using the same external concentrations as those chosen by Fisk (column 2 in the table), the results, presented as I/O ratios are similar for most scenarios since the size of the home we tested is similar to those estimated by Fisk. This includes our measured values for duty cycle, home air volume, etc. and the equipment properties that were looked up for the HVAC system and air filters installed.

We then calculated the indoor concentrations using the model for each time series value (column 4), which includes the experimental data mean values and standard deviations. The results are presented as I/O ratios in column 5. Presenting the mean I/O ratios for both the Fisk and Chan and test home inputs allows us to compare the outputs for model performance.

Table 4. Results of the Fisk Model for interventions of interest for residential indoor $PM_{2.5}$ concentrations of particles from outdoor sources.

Baseline or Intervention Code (Fisk and Chan 2017)	Fisk Mean Inputs Concentration ($\mu g/m^3$)	Indoor/ Outdoor Ratio Fisk	Test home Time Series (all days) Mean C ($\mu g/m^3$)	Indoor/ Outdoor Ratio Test Home
Co	56.9	-	319.14, SD=147	
B1	30.54	0.54	-	
i3	27.55	0.48	122.3 SD=56.3	0.38
i3.5	13.91	0.24	94.21 SD=43.4	0.30
i4	13.18	0.23	-	

Figure 6 presents the outdoor and indoor concentrations along with the model prediction for i3.5 (intermittent HVAC operation, high efficiency capture filter and portable air cleaner). The model predicted concentrations shown inside the home for the time period of the experimental conditions. The model predicted lower concentrations relative to the measured indoor concentrations for the first part of the experiment, but after the air cleaner was turned on beginning on September 16th, the model performed relatively well compared to measured concentrations.

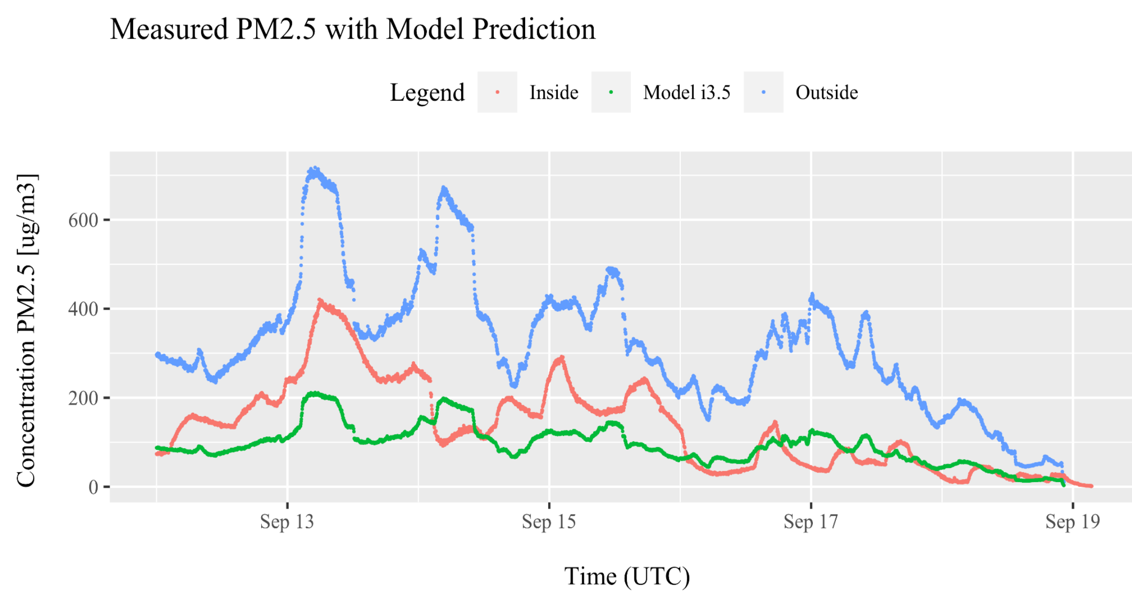

Figure 6. Raw $PM_{2.5}$ concentrations measured with the Clarity Node outdoors (blue) and indoors (red), with model i3.5 prediction indoors (green).

Figure 7 presents the model results for the indoor/outdoor ratio of $PM_{2.5}$ concentration with two model configurations; i3 includes intermittent HVAC operation with a high efficiency filter and i3.5 includes intermittent HVAC operation, a high efficiency filter and a portable air cleaner. The model predicted indoor/outdoor ratios for the time period of the experimental conditions. The experimental time series I/O ratio is presented in blue (mean values 0.38 for intermittent HVAC operation and 0.30 for intermittent operation + portable air cleaner), and the model prediction i3 I/O ratio is presented in red (mean 0.38), and the model prediction i3.5 I/O ratio is presented in green (mean 0.30).

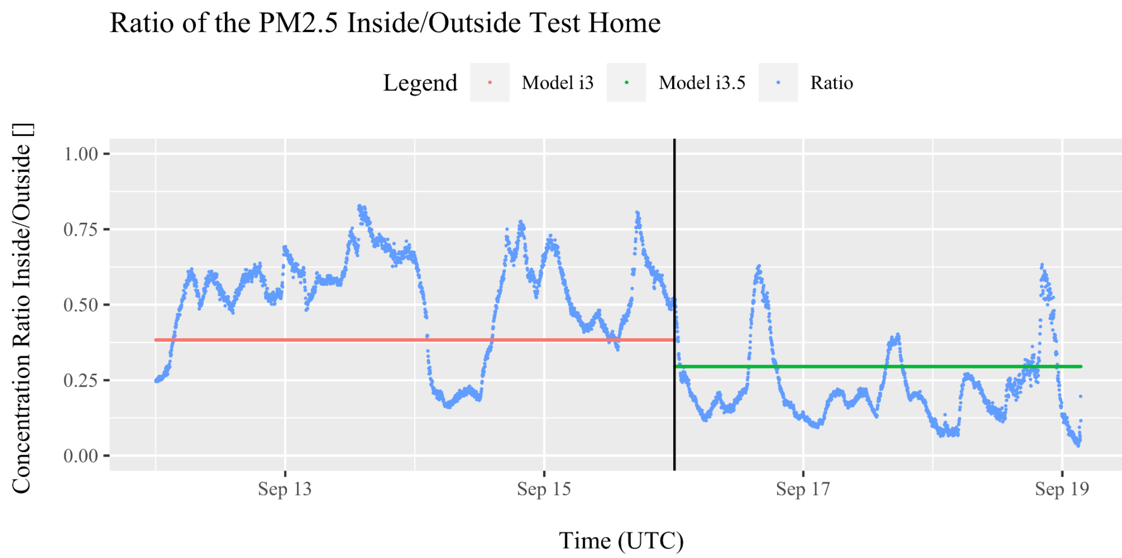

Figure 7. Time series I/O ratio as measured in the physical experiment is presented in blue. The red horizontal line is the model prediction under condition i3 and the green horizontal line is the model prediction under condition i3.5. The black vertical line denotes when the portable air cleaner was turned on.

Model Fit

Models i3 and i3.5 were evaluated for goodness of fit using the R^2 method. In this method, a least squares regression fit was used to quantify how a model might perform relative to a raw dataset to measure the impact of the interventions (May, Dixon and Jaffe, 2021). The output of the Fisk & Chan (2017) model provided one I/O ratio for the entire experimental period. To compare outputs for each model, the measured indoor and outdoor concentrations were plotted, relative to the modeled performance. Model i3 R^2=0.31, indicating there is opportunity to improve the Fish & Chan model to better fit measured data. Model i3.5 R^2=0.88, showing that the measured performance of the intermittent HVAC and the portable air cleaner was closer to the modeled estimates.

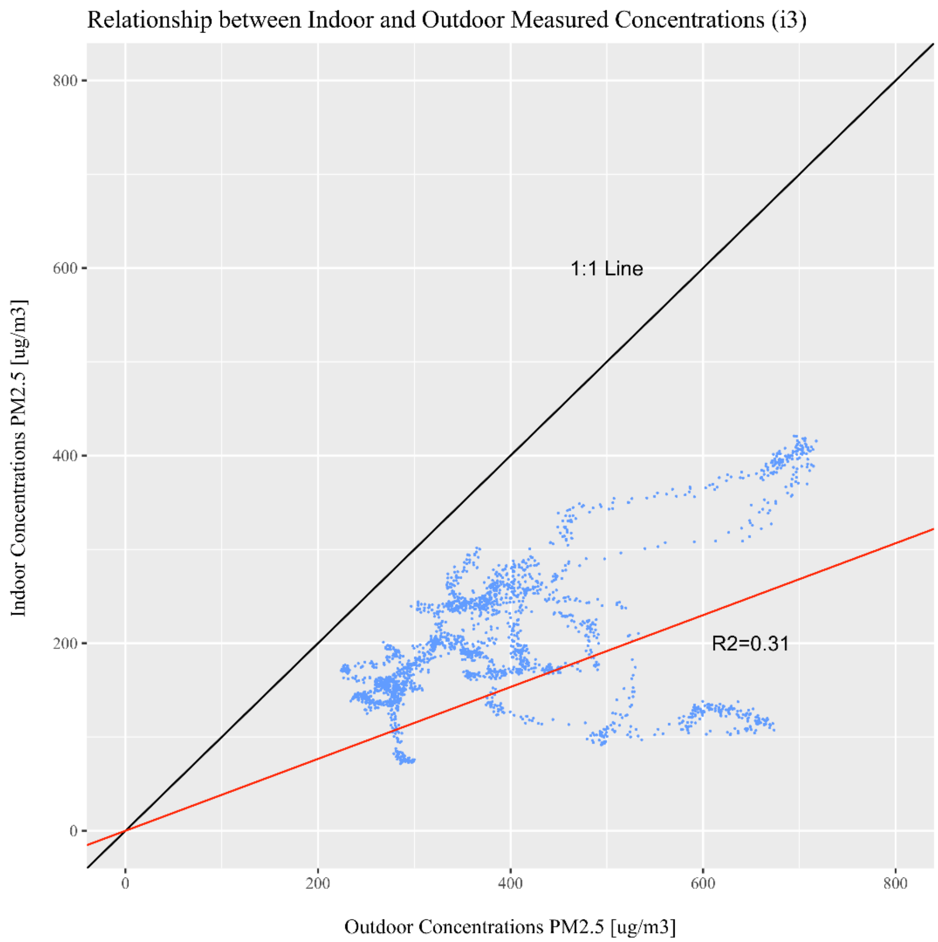

Figure 8. R^2 calculation for model i3. Experimental indoor and outdoor $PM_{2.5}$ timeseries data plotted with regression using modeled values. R^2 value for this model is 0.31.

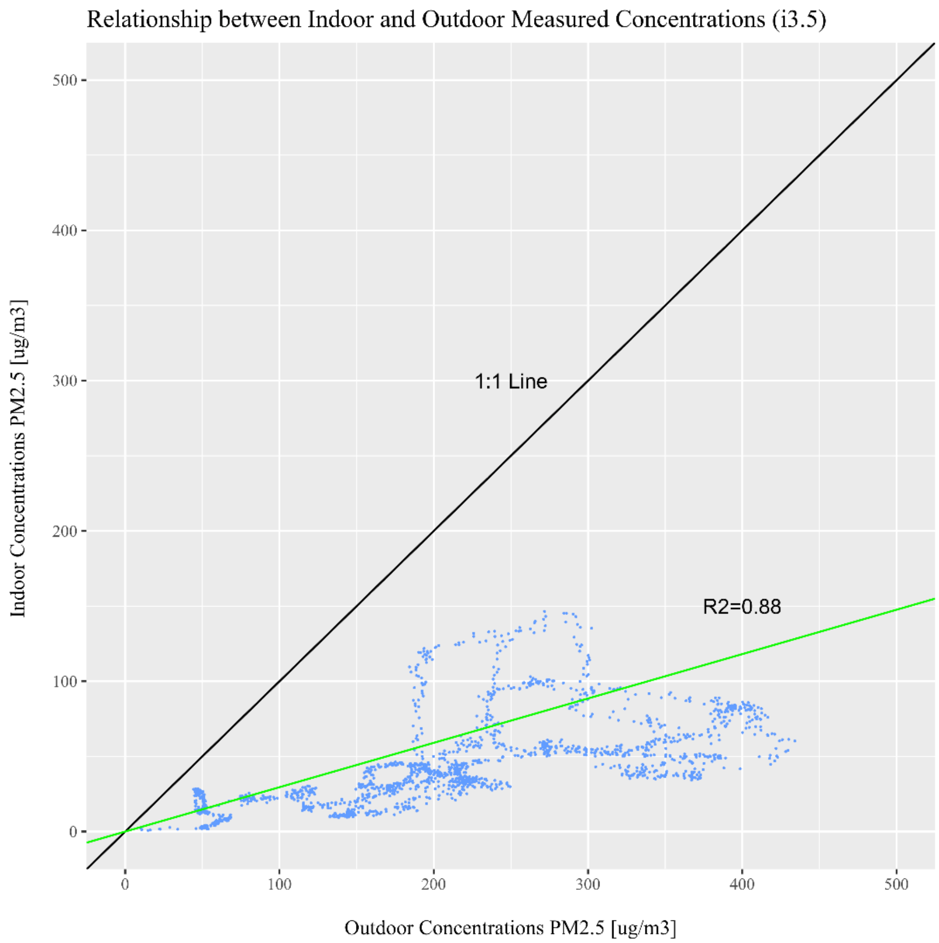

Figure 9. R^2 calculation for model i3.5. Experimental indoor and outdoor $PM_{2.5}$ timeseries data plotted with regression using modeled values. R^2 value for this model is 0.88.

Discussion and Conclusion

The goal of this study was to perform an experimental assessment of the indoor air quality model developed by Fisk and Chan (2017) using data gathered from a home in Portland, Oregon during an extreme wildfire event in 2020, when outdoor concentrations of $PM_{2.5}$ reached historic levels. Understanding expected building performance and occupant exposure risk during smoke events is an important public health issue, particularly as wildfire events become more prolific and exacerbated by climate change. Older, underperforming building stock with leaky enclosures are at particular risk for degraded IAQ from wildfire smoke. During the period of study, mean outdoor concentrations of $PM_{2.5}$ were measured at 277 ug/m^3, reaching as high as 717 ug/m^3 on September 13th 2020. Indoor concentrations reached 421 ug/m^3, with a mean concentration of 124 ug/m^3. I/O ratio of PM2.5 peaked over 0.75 two times during the study period.

A simplified version of the Fisk and Chan model was modified to represent the experimental test home characteristics, the HVAC system operations, and the portable air cleaner operation. The model performed well using the average assumptions about building characteristics determined by Fisk and Chan (2017). Although the smoke concentrations during the experiment time frame were an order of magnitude higher (mean 124 $\mu g/m^3$) than those used during the model development (mean 56.9 $\mu g/m^3$), the reduction normalizations predicted the experimentally observed conditions fairly well.

The model assumptions about performance of a high efficiency HVAC running intermittently (model condition i3) overpredicted the benefit of the upgraded HVAC filter in the system (R^2=0.31). It may be appropriate to further examine the assumptions for filtration performance in heavy smoke conditions like those observed during the experimental work.

The benefits of a portable air cleaner with a high efficiency HVAC (model condition i3.5) were more closely predicted during the measured event (R^2=0.88). The performance of the portable air cleaner during a heavy smoke event resulted in reduced concentrations consistent with the Fisk and Chan model. However, the smoke concentrations inside the home are still very high and represent a large public health risk associated with wildfire events in the Pacific Northwest. When the significant cost of a portable air cleaner is considered, it is likely that most lower income households would be at much higher risk. Additionally, only about 50% of homes in Portland Oregon have central air conditioning systems (data presented in paper 1 of this dissertation), which means that a significant number of homes do not have the option to run HVAC to filter indoor air, unless their air handler has a central whole-house fan.

We can conclude that the assumptions and model structure developed by Fisk and Chan (2017) are robust for estimating air quality in homes, but further investigation of the model performance in real systems is appropriate. The Fisk model assumptions are well documented and easily modified by other authors for large data sets. The building stock assumptions used are also adequate representations for our test home, resulting in relatively good approximations if no other information about the home and operation is known. We did not verify the cost and health aspects of the Fisk and Chan model.

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Chapter 4. Housing Inefficiency and Energy Poverty: How Building Characteristics Impact Energy Burdens in Low-Income Housing

Introduction

In the United States, buildings account for 40% of total energy consumption (U.S. EIA, 2018), which amounted to approximately 228.5 million metric tons of CO_2 equivalent in 2016 (U.S. EPA, 2019). According to the U.S. Energy Information Administration's Residential Energy Consumption Survey (RECS), total energy expenditures in the United States are approximately $218 billion annually, an average of $1,900 per household (U.S. EIA, 2018b). The energy burden, defined as the percentage of income spent on energy resources varies dramatically depending on socio-economic strata. While the average U.S. urban household spends 3.5% of its income on energy, urban low-income and African American households spend 7.2 and 5.4% respectively (Graff & Carley, 2020), highlighting the chronic disparity between populations. The amount of consumption and expenditures is not trivial; previous analysis has found that low-income residents spend approximately $20 billion on energy expenditures per year, amounting to approximately 8.6% of residential energy use (Hernández & Bird, 2012). In the 2015 RECS, 37% of US households reported they experience energy insecurity and 25% reported reducing or forgoing medicine or food to pay for energy costs (U.S. EIA, 2018).

There is a long history of programs improving energy efficiency through upgrading low performing homes and subsidizing low-income utility bills. The U.S. Department of Energy (DOE) funds the Weatherization Assistance Program (WAP), an energy efficiency grant program aimed at improving low-income housing stock, administered by states and local governments to income-qualified households. The WAP has been shown to increase thermal comfort and decrease energy use and expenditures (Schweitzer, 2005), however, these programs struggle to get abundant participation (Fowlie, Greenstone, & Wolfram, 2015). Likewise, energy subsidies are also commonly used to support low-income household energy costs. Subsidy programs play a role in maintaining affordable housing for low-income occupants by offsetting energy costs of a household. However, energy subsidies do not address the larger environmental concerns related to the overall building energy footprint, and unintentionally increase peak energy demand (Sherwin & Azevedo, 2020). Furthermore, subsidies that are not well targeted to low-income communities end up benefitting higher income earners (Allcott, Knittel, & Taubinsky, 2015).

Although programs have had success in achieving energy savings of the existing building stock, the general goals of policy to slow power system expansion and provide cost-effective approaches to achieve modest gains in efficiency have led to mediocre results (Lutzenhiser, 2014). The focus on inexpensive upgrade measures targets the "low-hanging fruit" in terms of energy efficiency, does not result in high performance housing stock, and does little to reduce the acute climate-related exposure risk of low-income households. In addition, many argue that energy efficiency policies are positively related to energy consumption through unintended incentivization (Adua, Clark, & York, 2021). Further, household behavioral change is a fundamental necessity for spurring increased energy efficiency in residential buildings; successful programs combine technological and behavioral interventions, which is often difficult for low-income families

(Abrahamse, Steg, Vlek, & Rothengatter, 2005; Gamtessa, 2013; Lutzenhiser, 1993; McAndrew, Mulcahy, Gordon, & Russell-Bennett, 2021). While increased investment in low-income program development has occurred, significant barriers still exist, including combining measures to achieve deeper energy savings from a whole-house perspective (Hoicka, Parker, & Andrey, 2014; Less & Walker, 2014). In low-income homes, barriers are further exacerbated, and while federal and regional programs exist, reaching those most in need has long been difficult (Drehobl and Ross, 2016; Ross et al., 2018).

Climate change adds a potentially compounding factor to existing inequities in the housing energy system. As climate change progresses, causing heat events to increase in duration and intensity, the energy consumption profile of buildings will change, resulting in increased cooling loads and peak demand periods (Shen, 2017; Wang & Chen, 2014). Low-income individuals, their households, and homes are more impacted by climate disasters due to location of residence, home construction practices, and building characteristics (Fothergill & Peek, 2004; Masozera, Bailey, & Kerchner, 2007). Furthermore, elderly, minority and low-income communities have higher mortality risks associated with extreme heat (Hondula et al., 2015). The risks of burden, both energy-based and climate-based, poses larger acute threats for low-income households and underscores the need for equity-based solutions that go beyond currently available policy mechanisms.

We surmise that energy burdens are nuanced, going beyond the traditional characterization of a disproportionate allocation of financial resources on energy expenditures (Hernández & Bird, 2012). Energy burdens are used as an umbrella term, but there are non-trivial problems with categorizing the varying factors associated with burdens in one frame. We argue that chronic inefficiency of the building structure and components is a factor when considering energy burdens, and that chronic energy insecurity prevents a household from responding to, and amplifies the negative impacts of, acute needs as a result of extreme weather or other climactic conditions. There is a need to better understand what the impacts of existing chronic energy burdens, coupled with acute climate events pose on low-income communities, and how policy mechanisms need to shift to address these risks. We argue that the advancement of climate change and associated climatic events requires a systems-thinking approach to energy use in households and energy equity, and that the current policy mechanisms available will not be enough to protect vulnerable populations against acute climate risk. Using two novel, robust datasets, we ask the following questions: 1) what ways do housing characteristics and energy consuming technologies affect the likelihood of energy burdens? 2) what are the disparities associated with housing characteristics between low-income homes and the general population? and 3) how do energy burdens differ in low-income housing compared to other housing types?

The role of building characteristics in defining energy burdens

Recent years have seen increased focus on energy burdens, energy equity and energy justice in the residential building sector (Drehobl et al., 2020; Kontokosta, Reina, & Bonczak, 2020; Lewis, Hernández, & Geronimus, 2020; Reames, 2016b). Acute and chronic factors that impact energy security have been observed, and this study relies on previous work to identify how individual building characteristics inform chronic energy burdens (Jessel et al., 2019). Understanding the nuances associated with energy burdens is important because chronic energy insecurity can prevent a household from responding to, and amplify the negative impacts of, acute needs as a result of extreme weather or other climactic conditions.

There are many internal and external factors that impact the vulnerability of low-income households. Figure 1 presents a conceptual model that identifies exposure risks for vulnerable communities, focused on how the built environment and surrounding landscape impacts exposure risk for home occupants. Low-income and vulnerable households have increased overall exposure risk related to heat and wildfire smoke as a result of increased energy burdens (Samuelson et al., 2020). The chronic risk associated with inefficient housing poses a larger equity issue associated with a just energy transition (Lewis et al., 2020).

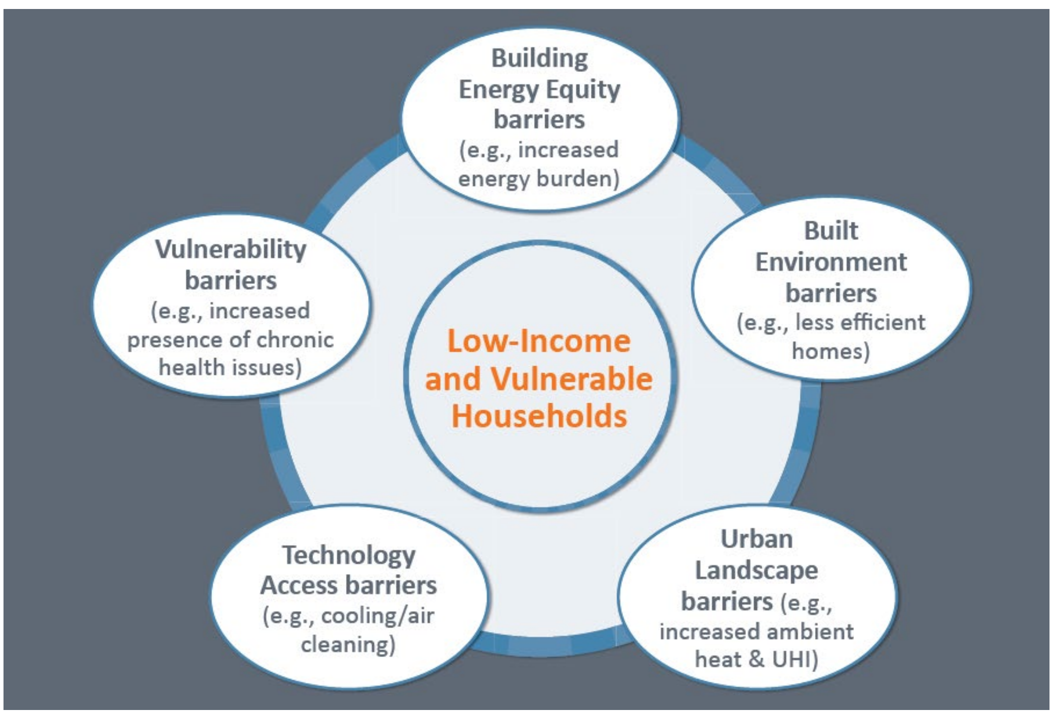

Figure 1. Factors impacting energy equity in U.S. housing stock.

Methods

Data

There are two datasets that are employed in this study. The first uses a robust, novel dataset from the U.S. Department of Energy's (DOE) Home Energy Score program, that represents 16,731 single family homes in Portland, OR. The DOE Home Energy Score (HES) program was launched in 2012 to provide a low-cost alternative to full existing home energy audits, similar to gasoline efficiency ratings for a car. The HES is targeted to homeowners and homebuyers as a simple way to understand the energy performance of a building. To determine a HES, a trained third party assessor enters building characteristics into a software tool which then runs an algorithm using the E+ building energy modeling tool (U.S. Department of Energy, 2017). The "Score" is designed to provide an overview of the home's energy performance, based on the building inputs added to the tool.

The City of Portland, Oregon has a large sample of HES due to a city-wide program enacted in 2016. The program requires nearly every home seller within the City of Portland limits to include the Home Energy Score and Report in any listing or public posting about the home that becomes available to homebuyers. The Green Building Registry is a publicly available database developed by a local non-profit, Earth Advantage, to aggregate and share 3rd-party verified data on homes from across the U.S. This study leverages the inputs used to the generate the score, not the actual score output or other programmatic information.

The second dataset was given to the researchers from the Community Energy Project, a nonprofit low-income residential energy efficiency program in Portland Oregon (n=107). The program provides free home services that are focused on increasing health, safety and energy efficiency for income-qualified households. The program uses the U.S. Department of Energy's Home Energy Score as an analysis tool to identify energy savings opportunities and to provide guidance regarding efficiency measures that will save the most energy and cost for occupants. The scores were taken between 2018-2020 and mirror the inputs used in the greater HES database. Summary data for program participants is presented. Table 1 presents the data inputs gathered for each home in the database which are used to determine a score and are used for this study.

Table 1. Synopsis of data included in the HES database.

Home Characteristics	**HVAC Characteristics**
Address	Heating system type
Orientation	Cooling system type
Year built	Duct location
Conditioned floor area	Duct sealing
# Stories	HVAC efficiency (SEER/AFUE)
# Bedrooms	Fuel type
Floor to ceiling height	Renewables present
Envelope Characteristics	**Energy Metrics**
Blower door performed	Current Home Energy Score
Air sealing present	Energy costs
Envelope leakage (CFM)	Energy use intensity
Roof area	Energy use (kwh/therms)
Roof material	Energy cost (USD)
Roof color	**Wall/Window Construction**
Foundation type	Wall type
Foundation insulation	Wall insulation
Water heating	Window/skylight type

Study Area

The city of Portland, Oregon is the focus of this study. The City is the most populated metropolitan area in Oregon and one of the larger cities on the west coast of the U.S. The average temperature ranges from 4.7 °C (40.4 °F) in December to 20.8 °C (69.5 °F) in August (National Oceanic and Atmospheric Administration, 2017). The residential sector is dominated by single-family detached residential buildings, which is the focus of this study. The city is considered a marine climate, categorized by mild winters, dry summers and moderate humidity levels, which translates to climate “Csb” on the Köppen-Geiger climate map (Kottek et al., 2006). The large, general sample of HES is representative of the entire city (Figure 2), with the subset of low-income homes concentrated on the East side of the Willamette River, in NE, SE, and N Portland (Figure 3).

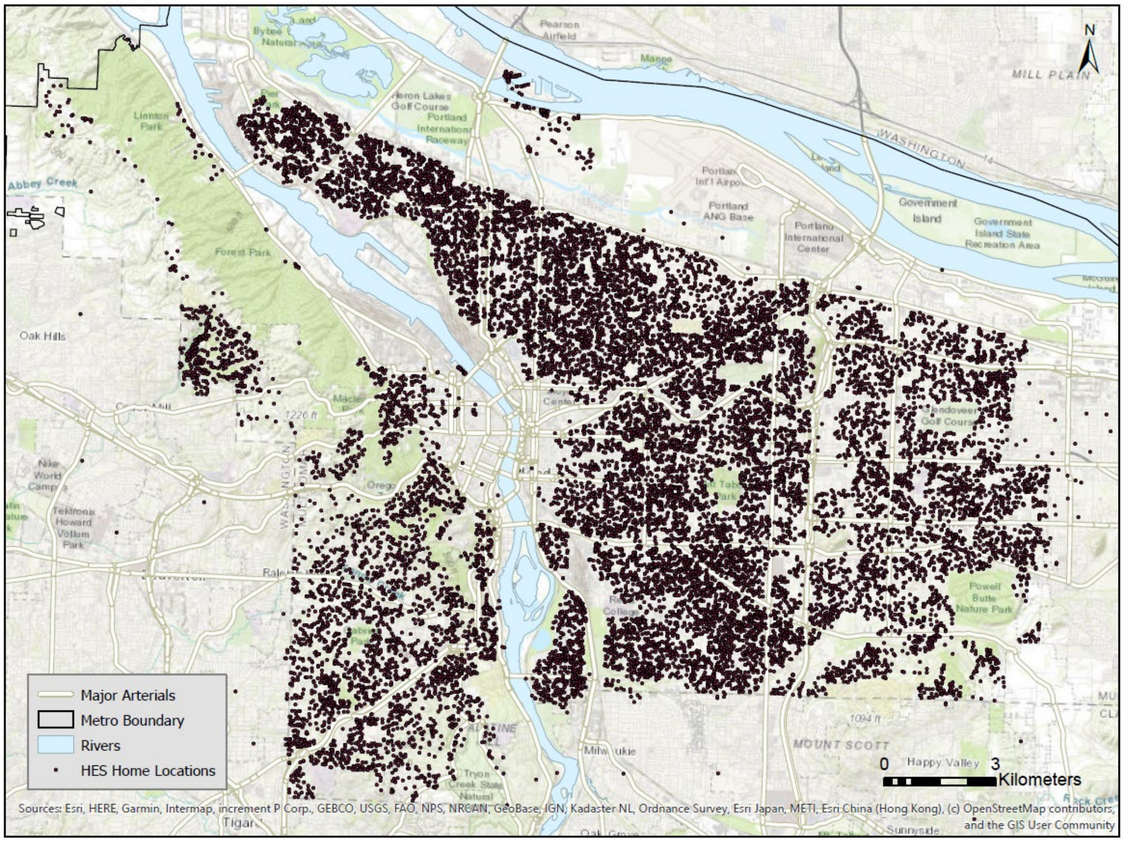

Figure 2. Home Energy Score data sample throughout the city of Portland.

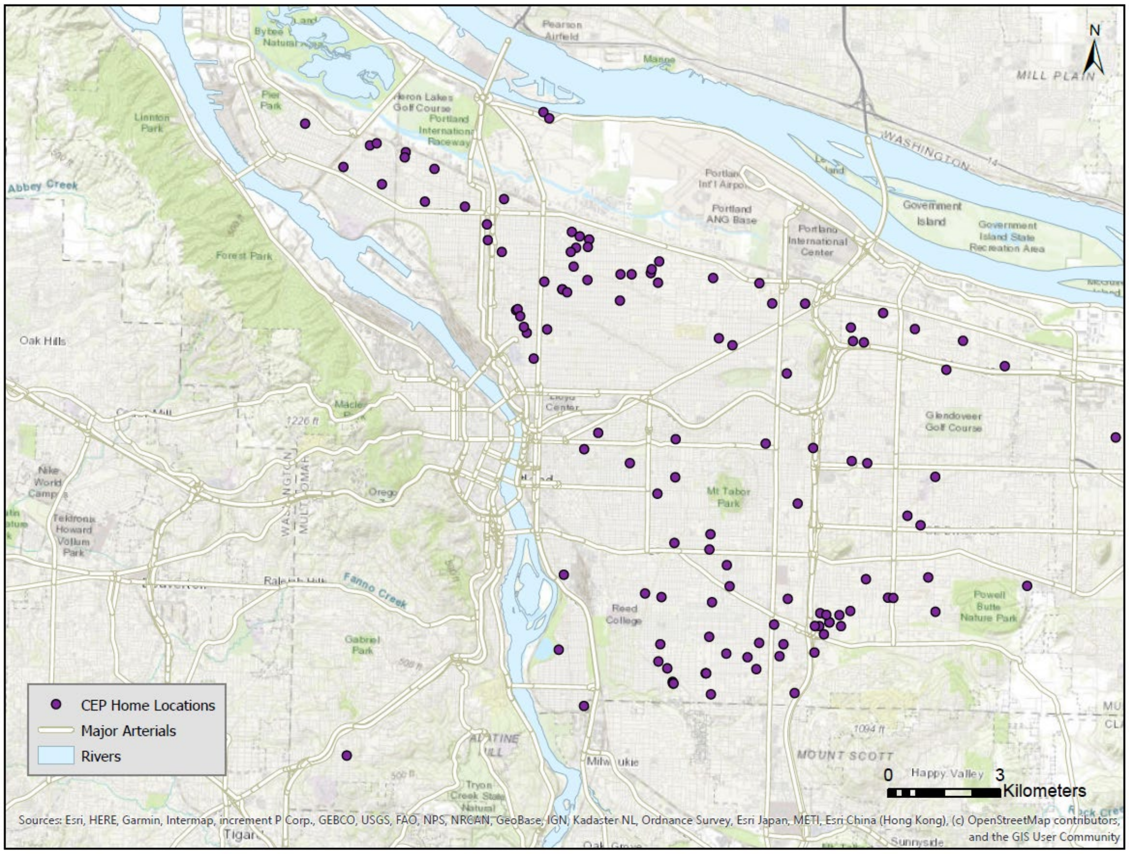

Figure 3. Locations of low-income residential building data sample in Portland, Oregon.

<u>Program Data, Statistical Analysis, and Double Burden Methods</u>

Summary statistics for the general population and low-income sample are presented for both datasets. The low-income sample includes demographic data collected by program administrators about each household that participated in the energy retrofit program.

To compare the two datasets, a Welch's two sample *t*-test was calculated to measure statistical significance in the variance in mean values, an approach which has been used in previous energy efficiency study (Jain, Taylor, & Peschiera, 2012). The null hypothesis for the Welch's *t*-test assumes the two datasets mean values do not differ.

When they differ, the null hypothesis is rejected (West, 2021). The software package R was used with the *t*-test package (R Documentation, 2021). For each set of parameters in the datasets, a separate *t*-test was calculated for each variable. For example, the floor area of all the homes in the HES dataset for Portland was compared to the floor area of the CEP homes. To measure the size effect of the difference, a Cohen's *d* was calculated (Cohen, 1992). The Cohen's *d* test measures how many population standard deviations there are between the two means in a given dataset, the results of which communicate the "effect size," measured by the *d* value, which adds further granularity into the *t*-tests by identifying the practical significance of the difference in mean values.

To determine household energy burdens, the percent of annual household income spent on energy was calculated. The household energy cost ($/year) for each home is an output of the Home Energy Score database for each house with a score. To measure the energy burden for the general sample, the median household income (MHI) by block group was appended to each datapoint (U.S. Census Bureau, 2019). For the low-income sample, the MHI was reported directly by the household.

Results

Self-Reported Low-Income Home Demographics

According to the US Census, median annual household income for the Portland Metro region was $75,300 USD in 2019 with approximately 9% of households under the federal poverty level ($20,600 for a family of four in 2020), and an additional 12.4% considered low income (U.S. Census Bureau, 2019). Breakout of Census MHI by block group is presented in Figure 4. The Community Energy Project collected voluntary demographic data for participants in the program, which resulted in detailed demographics for 58 homes. Median monthly income reported by this subset of the low-income sample was $1,900 USD ($22,800 USD annual), amounting to only 30% of the region's median household income. Median occupant age was 65, veterans represented 12% of the sample, and 65% of respondents indicated they had a disability (Table 2 and 3).

Table 2. Summary of Low-Income demographic characteristics.

Low-Income Household Characteristics (n=58)			
	Mean	**Median**	**Range**
Occupant Age	62	65	35-86
Household Size	2.3	2	1 -- 6
Monthly Household Income (USD)	2182	1900	825-5000
Monthly Household Income as % of Regional Median	35	30	13-80

Table 3. Low-income sample disability status

Low-Income Veteran/Disability Status (n=58)			
	Yes	**No**	**Prefer not to answer**
Veteran	12%	86%	2%
Disability	56%	40%	4%

Figure 4 presents the location of CEP homes and median household income for the city reported by the U.S. Census, by census tract. Many homes are in areas that are traditionally considered low-income neighborhoods or areas that are rapidly gentrifying. Lighter colors indicate lower MHI reported by the census.

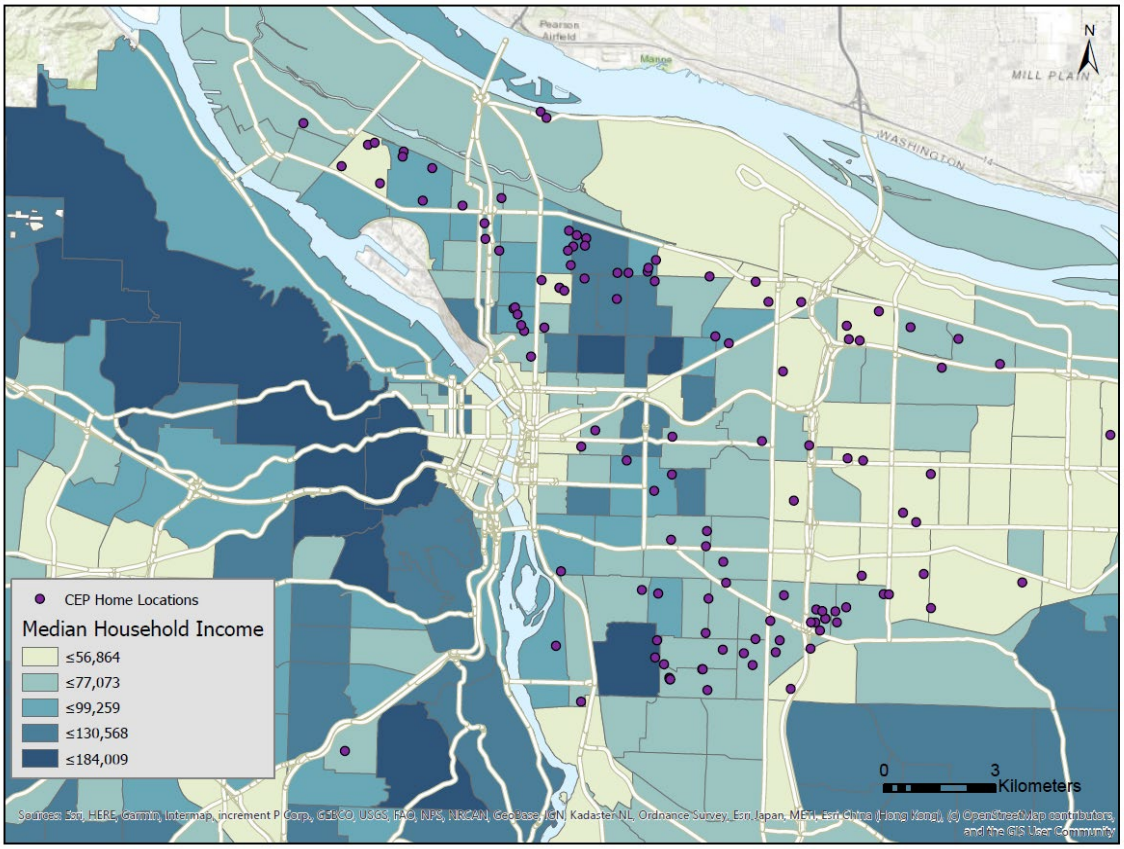

Figure 4. Breakdown of household demographics for the low-income sample. Median household income reported in USD. (Baseline MHI from U.S. Census, American Community Survey 2020).

Self-reported race/ethnicity data was collected by the CEP and is reported in Figure 5 (n=58). 37 respondents that agreed to share data identified as Black/African

American, 17 identified as White/European American, 2 Hispanic/Latinx, Asian and Slavic. Two respondents did not provide information.

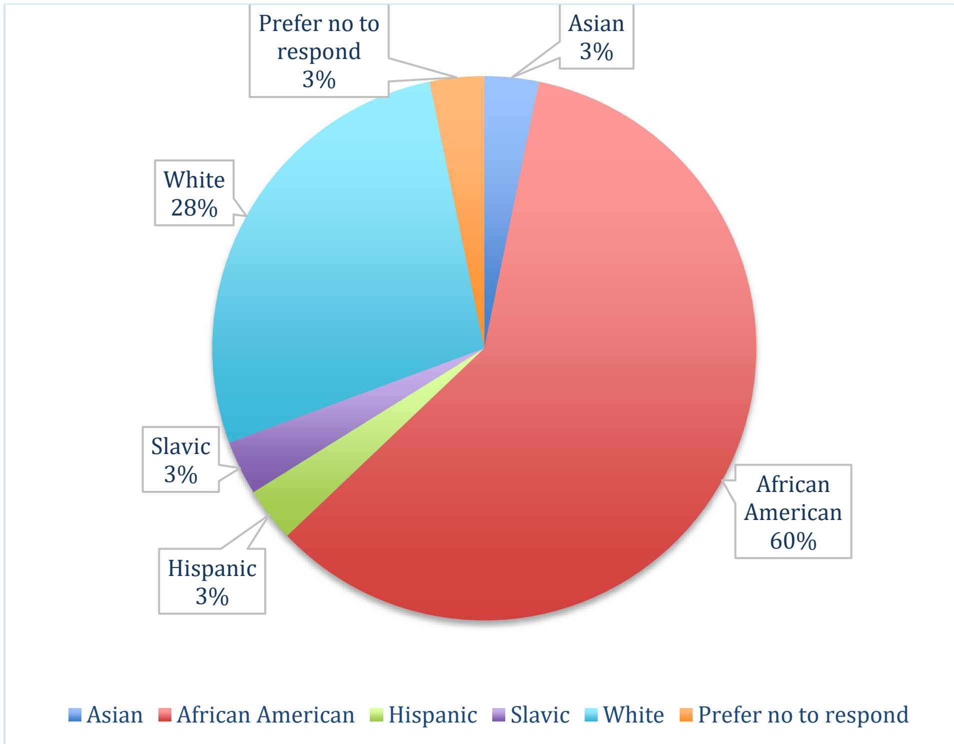

Figure 5. Breakdown of race/ethnicity of low-income home sample as reported by the CEP participants.

<u>Summary Data & Statistical Tests</u>

Summary of energy performance statistics are presented in the following tables. The General Portland Sample includes the general HES dataset, and the Low-Income Sample includes HES homes from the low-income program dataset.

Table 4 presents general building and energy consumption data from both groups. Mean, median and range values are presented along with results from the Welch's *t*-test and Cohen's *d* test. Statistically significant differences in home size, energy use intensity (EUI) and energy costs were observed, and Cohen's d estimates were small, indicating the effect size between the two samples was rather low. Home age, number of bedrooms, total source energy use and CO_2 emissions were similar between samples.

Table 4. Residential building characteristics for both data samples and t-test results. SI measures presented, with U.S. customary units presented in parentheses.

Residential Building Characteristics for total Home Energy Score sample and low-income home sample										
	General Portland Sample			**Low-Income Sample**			**Welch's t-test**		**Cohen's d**	
	n=16,731			**n=107**						
	Mean	Median	Range	Mean	Median	Range	t	p-value	d	Interpretation
Year Built	1955	1952	1824 – 2020	1955	1953	1891 - 2018	0.1803	0.8572	0.017	Negligible
Home Size: m^2 (sq ft)	177.3 (1,908)	161.7 (1,740)	31.8-4,369.3 (342 – 14,335)	138.2 (1,488)	124.0 (1,335)	45.3-350.3 (488-3,771)	7.046	<.0001 **	0.466	Small
Bedrooms (#)	3	3	2 – 4	3	3	1 -- 6	-	-	-	-
Base EUI: kWh/m^2 (kBtu/sq ft/yr)	368 (47.9)	338 (44)	0-783 (0-102)	427 (55.7)	411 (53.5)	207-729 (27-95)	-3.9754	<.0001 **	-0.431	Small
Total Source Energy: kW (MBtu/yr)	4.88 (142)	4.74 (138)	1.65-8.21 (48-239)	4.77 (139)	4.60 (134)	2.92-7.90 (85-230)	0.85638	0.3941	0.089	Negligible
Energy Costs ($/yr)	1,571	1,501	187 – 5,245	1,492	1,450	704 – 2,695	1.7937	0.0522 *	0.201	Small

CO_2 Emissions: kg/yr (lbs/yr)	5,524.8 (12,180)	5,344.7 (11,783)	13,46.7-9,787.2 (2,969-21,577)	5,444.1 (12,002)	5,210.9 (11,488)	2,948.8-8,542.5 (6,501-18,833)	0.56485	0.5736	0.055	Negligible
Energy Burden (%)	2.5	2.2	0-16	6.6	6.2	1.6-17	-7.077	<.0001 **	-3.34	Large

* Significant at 95% confidence level

** Significant at 99% confidence level

Table 5 presents fuel type used by both samples. Statistical significance was observed in the percentage of homes using electricity (p=0.077) although the effect size is small. For fuel oil, a higher percentage of low-income homes use fuel oil as an energy source (p=<.0001), and the effect size was observed to be medium, indicating a that low-income homes are more likely to use heating sources powered with fuel oil, which is an indication of old, inefficient, carbon intense equipment.

Table 5. Fuel type for both data samples and t-test results. SI measures presented, with U.S. customary units presented in parentheses.

Site Energy Type in Homes												
	General Portland Sample				**Low-Income Sample**				**Welch's t-test**		**Cohen's d**	
	n=16,731				**n=107**							
	% of Homes	**Mean**	**Median**	**Range**	**% of Homes**	**Mean**	**Median**	**Range**	**t**	**p-value**	**d**	**Interpretation**
Electricity (kWh/yr)	97	9435	9050	3638-23253	84	8832	8437	5001-22011	1.7885	0.0771	0.211	Small

Natural Gas (therms/yr)	84	551	529	29-1263	63	576	557	137-1126	-0.91782	0.362	-0.109	Negligible
Fuel Oil (gal/yr)	4	452	422	41-1662	9	308	310	176-416	5.5359	0.0004 *	0.723	Medium
Propane (gal/yr)	0.1	317	188	94-554	0	na	na	na	-	-	-	-
Cord Wood (#/yr)	0.3	2	1	3-Jan	1	1	1	1	-	-	-	-
Pellet Wood (lbs/yr)	0.1	3103	2989	796-5415	0	na	na	na	-	-	-	-

* Significant at 99% confidence level

Energy Burden Results

Table 6 presents the comparison of energy burdens between the general Portland sample and the low-income sample. Energy burdens are observed to be higher in low-income homes (p=<.0001), with a large effect size, as seen by the Cohen's *d* results. Figure 6 presents the distributions of energy burdens in graphical form.

Table 6. Energy burdens in the general Portland HES dataset and the Low-Income data set, Welch's *t*-test and Cohen's *d* results.

Energy Burdens										
	General Portland Sample n=16,731			**Low-Income Sample n=107**			**Welch's *t*-test**		**Cohen's *d***	
	Mean	**Median**	**Range**	**Mean**	**Median**	**Range**	**t**	**p-value**	**d**	**Interpretation**
Energy Burden (%)	2.48	2.23	0-16	6.55	6.16	1.6-17	-7.08	<.0001*	-3.34	Large

* 99% confidence level.

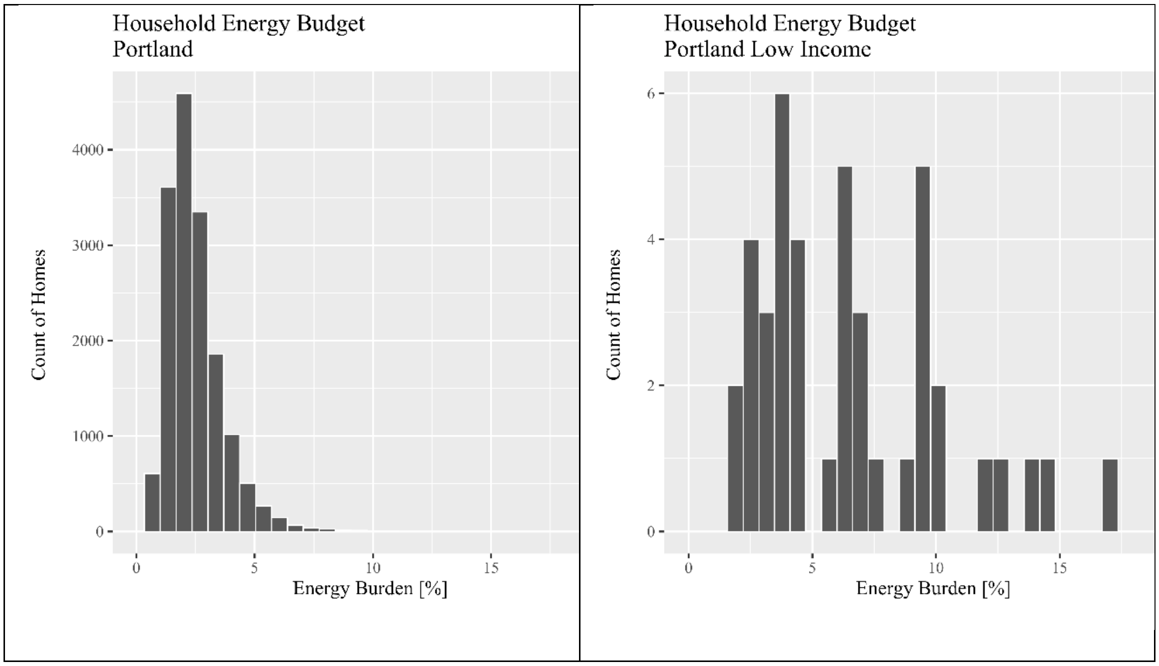

Figure 6. Energy burdens calculated for each population. The left graph presents the total HES sample, using Census MHI by block group to calculate total burden. The right graph presents energy burdens calculated from HES outputs for total energy costs and uses the self-reported household income for each home in the low-income sample.

Comparisons of EUI were statistically tested (p=<.0001, small effect size) and are presented graphically here to identify the role of EUI in energy burdens. Figure 7 presents the difference in EUI, and while the effect size was found to be small, the differences in mean, median and range values add further nuance to the energy burden analysis. Many analyses use EUI as a proxy for energy efficiency (Kontokosta et al., 2020; Lewis et al., 2020; Reames, 2016b), and the findings here when combined with the energy burdens illustrate how burdens compound in low-income households.

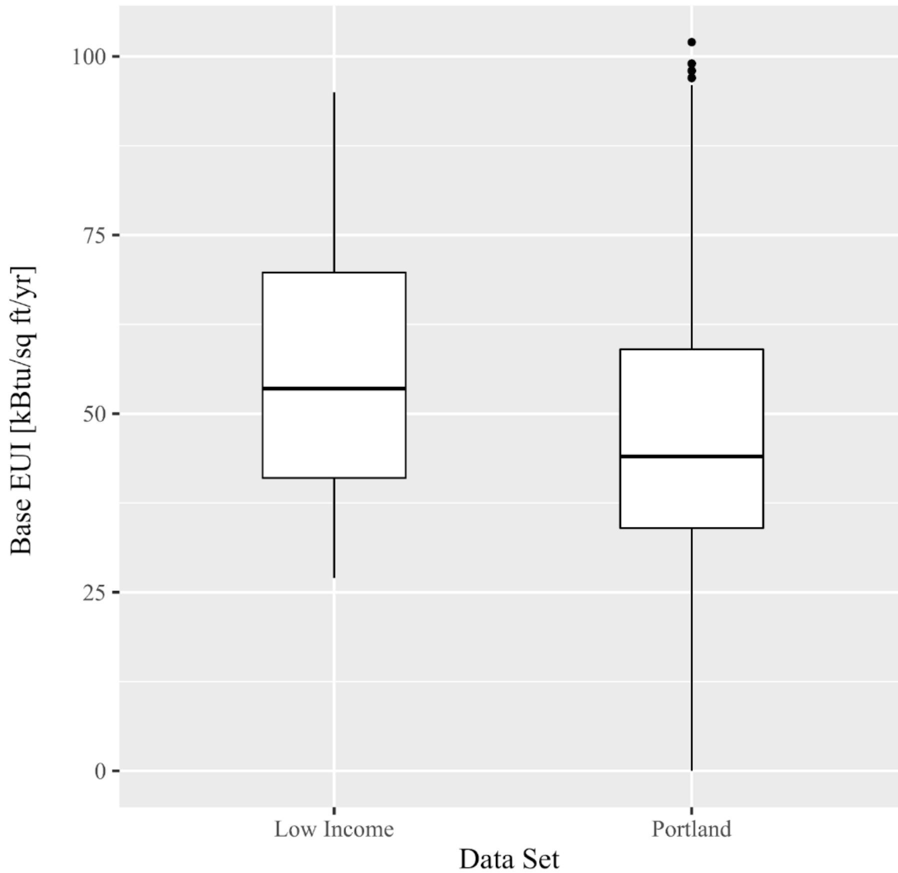

Figure 7. EUI comparisons between low-income (left) and general Portland HES populations (right). Boxes show interquartile range with mean values denoted by the black bar in the box and whiskers are limit values representing the 25th-75th percentiles, with outliers presented as circles outside the whiskers.

Type of heating and cooling equipment in general sample and low-income sample is presented in Tables 7 and 8. Baseboard heat, which tends to have lower resource efficiency (Dillon, Dzombak, & Antonopoulos, 2019), is more prevalent in the low-income sample and fewer low-income homes have central air conditioning. The distribution of other HVAC systems is similar between samples, with the penetration of heat pumps still low, indicating an opportunity to increase prevalence of heat pumps in residential buildings.

Table 7. Heating equipment in sampled homes

HVAC Heating Equipment		
	General Portland Sample (%)	Low-Income Sample (%)
Baseboard	8	19
Boiler	2	1
Central Furnace	82	72
Heat Pump	4	3
Mini Split	4	3
Wall Furnace	1	1
None	0	1
Secondary Heating System?	14	13

Table 8. Cooling equipment in sampled homes.

HVAC Cooling Systems		
	General Portland Sample (%)	Low-Income Sample (%)
Heat Pump	4	3
Mini Split	4	3
Central Air Conditioner	42	37
None	50	55
No Answer	0	1

Secondary cooling system?	6	3

Heating and cooling system efficiencies are presented in Table 9. Efficiencies for electric systems are measured in heating seasonal performance factor (HSPF), seasonal energy efficiency ratio (SEER) and annual fuel utilization efficiency (AFUE) for gas systems. Energy Star Product Criteria requires systems to be >8.5 HSPF and >15 SEER[3] and 0.90 AFUE for gas furnaces[4]. Central forced-air furnace systems are used heavily in both samples and are significantly less efficient in the low-income homes. For electric-based systems, efficiencies trended higher in low-income homes, which provided heat pump retrofits for many households. No t-tests were performed for the equipment efficiency due to low sample size for each type of equipment in the low-income data set.

Table 9. Heating and cooling efficiencies by sample and fuel type

Heating and Cooling Efficiencies						
	General Portland Sample			**Low Income Sample**		
	Mean	**Median**	**Range**	**Mean**	**Median**	**Range**
Heat Pumps (HSPF)	8.89	8.5	7.6-10.6	8.7	8.8	8.3-9
Air Conditioner (SEER)	14.24	14	10-18	14.8	15	12.9-16.4
Gas Furnace (AFUE)	0.88	0.9	0.8-0.96	0.85	0.8	0.8-0.96

[3] https://www.energystar.gov/products/heating_cooling/heat_pumps_air_source/key_product_criteria

[4] https://www.energystar.gov/products/heating_cooling/furnaces/key_product_criteria

Discussion and Policy Recommendations

In summary, we found that that the average energy burden of the low-income sample was 7%, reaching as high as 17%, compared to an average of 3% for the general sample ($p=<.0001$, large effect size). We tested individual housing characteristics that contribute to the energy burden, finding that low-income homes have more HVAC systems that use fuel oil ($p=<.0001$, medium effect size), more use of baseboard heat and less efficient HVAC systems, and higher EUI, even though the homes in this sample have less average square footage ($p=<.0001$, small effect size). Additionally, low-income homes are marginally older compared the sample of all HES homes ($p=<.0001$, small effect size). The low-income households that agreed to share their demographics with researchers were found to have only 30% of the median household income of the region. Additionally, 60% of households identified as African American, with a median age of 65. 12% of participants were veterans and 56% had a disability.

The overall difference in EUI between samples was statistically significant with a small effect size. The spread of the data in both samples show that the 75th percentiles trend much higher in low-income homes, and no outliers are present in on the lowest 25th percentile, compared to the general HES sample. This highlights a general inefficiency in the low-income sample. Although the Cohen's d effect size was small for EUI, we surmise that the results of the analysis measuring individual building measures (HVAC, fuel type, energy burden) combines with the EUI findings to add nuance into the contributions of inefficient housing on energy burdens. EUI is an important metric because it has been found to be significantly higher in low-income areas (Tong et al., 2021). EUI is can also be an indication of inefficient housing stock, which this analysis supports (Bednar, Reames, & Keoleian, 2017).

Low-income program participants' socio-demographic distributions trend similar to energy equity discourse, and further highlight the need for energy justice in housing (Bouzarovski, 2018; Jenkins et al., 2020). These households are more susceptible to energy poverty, have higher exposure risks and are more vulnerable to climate-related exposures (Farbotko & Waitt, 2011; Liu et al., 2015; Taylor et al., 2015, Nelson & Gebbia, 2018). Low-income elderly households use more energy per capita, with only about 7% of income-qualified households receiving utility bill assistance (Bruce Tonn & Eisenberg, 2007).

The modern use of the term "energy transition" refers to the large-scale societal transformation from carbon-based energy systems to decarbonized ones. Buildings play a fundamental role in decarbonization strategies due to their high energy intensity and also because most technology end-use occurs in buildings (Grubler, 2012). In the residential sector, households that are energy poor are often forced to use underperforming equipment, or do not have access to advanced technologies. Results from this work suggest that low-income households can be the hardest hit when it comes to increased intensity of climate events and that policy mechanisms focused on low-income energy transitions are warranted. A recent review of articles in energy justice literature identified supportive financial structures, attention to local contexts, and collaborative procedure and decision making as primary recommendations for policy (Jenkins et al., 2020). Reames (2016b) noted the importance of community-based approaches to enhancing low-income participation in energy efficiency programs. Policy focused on marginal gains in building efficiency, or subsidies for energy utilities will not address inequities. The whole-building, deep energy retrofit approaches and advanced technology distribution programs that focus specifically on equity are promising advancements. Policy solutions aimed at promoting a social-science mechanism for energy policy design and advancing interdisciplinary discourse in energy efficiency have been proposed (Lutzenhiser, 1992; Moezzi & Janda, 2014; Sovacool et al., 2015; Sovacool, 2014). This analysis highlights the opportunities to leverage community-based approaches to energy efficiency, which we argue would support an energy justice framework for the residential building sector.

Future investigations should focus on an integrated climate and energy model scenarios to investigate long term impacts of chronic and acute burdens and how these burdens will shift as a result of climate change and on a spatial-temporal scale. Home Energy Score provides an opportunity to investigate city-scale opportunities for energy conservation by investigating neighborhood-by-neighborhood opportunities which can lead to aggregate approaches to retrofitting the housing stock (Antonopoulos et al., 2020). As the use of programs like HES progress, a focus on low-income areas could provide policy opportunities by fixing the homes that are in acute conditions, thus stabilizing neighborhoods and providing social and household benefits by keep communities intact and increasing resilience. Finally, this study was confined to owner-occupied low-income housing and did not consider renter-occupied housing. Integrating renter-occupied homes into energy burden analysis is an important consideration due to issues with split incentives, leading to marginal efficiency gains in rental units (Gillingham et al. 2012).

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Chapter 5. Conclusions and Implications

This research explored the impacts of extreme heat and wildfire on residential buildings, focused specifically on exposure risks related to energy performance and indoor air quality, and the complex influences that location and socio-demographics plays on residential energy use and energy burdens. These areas of focus culminate to provide insight into the impacts that climate change has on building occupants, measured by risk of exposure to extreme heat and degraded IAQ related to wildfire smoke. The research explored draws on previous empirical studies into urban heat island effects (Deilami, Kamruzzaman, & Liu, 2018b; Voelkel & Shandas, 2017; Yang, Qian, Song, & Zheng, 2016), IAQ in residential buildings and the impacts of wildfire smoke events (Fisk & Chan, 2017; Fisk, 2015; Henderson et al., 2005; Nazaroff, 2004; Persily, Musser, & Emmerich, 2010), energy equity & justice in the residential sector (Hernández & Bird, 2012; K. Jenkins et al., 2016; Tony Gerard Reames, 2016b), and the socio-economic, demographic, societal, and energy transition theory that influences energy use in residential buildings (Abrahamse & Steg, 2009; Lutzenhiser, 1993; Miller, Richter, & O'Leary, 2015).

Each paper presented with an over-arching research question, explored empirically with mixed methods. Research questions included the following:

1. On a city-scale, what are the relationships between increased ambient heat, building characteristics and energy use? How do these relationships vary on a spatial scale based on location within a city?

2. How do residential building characteristics and technology interventions impact exposure to heat and woodsmoke during extreme heat events and wildfires?
3. How do building characteristics, energy burdens and income impact exposure risk in residential buildings, and how are different populations impacted?

Research overview and contributions

Each paper explored systems related to energy use, exposure risk and resiliency in residential buildings. Specific contributions related to each paper include the following.

1. The research used a novel dataset provided by the U.S. Department of Energy, the Home Energy Score (HES), which provides building characteristics for over 15,000 residential homes throughout the Portland Metropolitan area (Chapter 2 and Chapter 4). Compared to other publicly available data, such as EIA Residential Energy Consumption Survey or the Northwest Energy Efficiency Alliance's Residential Building Stock Assessment, the use of HES provides an extremely granular view into residential building energy efficiency characteristics and supported detailed analysis into both energy burdens and the building characteristics that exacerbate them (Chapter 4).

2. This research expands our knowledge about $PM_{2.5}$ concentrations indoors during extreme wildfire smoke events, and the influence of intervention measures that includes a high-efficiency central HVAC filter, and a portable air cleaner (Chapter 3). Additionally, the data gathered from the physical experiment during the smoke event was used to assess previous modeling work, finding that one model

configuration developed by Fisk and Chan (2017) that evaluated a high-performance intermittent HVAC filter coupled with a portable air cleaner performed well, even when outdoor concentrations of $PM_{2.5}$ were extremely high.

3. Through a comparative study between a general sample of homes and homes associated with a low-income efficiency program in Portland Oregon, the research presents an analysis that includes both energy burdens, and individual building factors that contribute to chronic energy poverty, highlighting factors that culminate to impact equity in the residential sector (Chapter 4).
4. The city-scale distribution of installed air conditioning was explored relative to measured ambient air temperatures (Chapter 2).

Individual contributions of each paper

Chapter 2 summary and conclusions

Extreme heat events continue to emerge as serious threats to urban and social systems. Extreme heat from heat waves are the biggest cause for mortality in many cities and responsible for more deaths annually than any other form of extreme weather (Luber & McGeehin, 2008). In the urban environment, the uneven distribution of ambient temperatures creates urban heat islands, which are also becoming more prolific and exacerbated by climate change. Vulnerable communities are disproportionately exposed to urban heat, with low-income neighborhoods more likely to be located in hotter areas of the city (Hoffman et al., 2020; Wilson, 2020). During extreme heat events, access to air conditioning (AC) provides increased thermal comfort, and for many at-risk populations, is necessary to mitigate heat-related illness and mortality in homes (Barreca et al., 2016). This Chapter looked at the presence of AC and energy efficiency measures relative to the location of urban heat using statistical and spatial analyses, and a granular dataset that includes data for over 16,000 single-family residential buildings coupled with detailed temperature data in Portland, Oregon.

The percentage of all homes in the sample with installed central AC systems is 53%. We then binned the homes in two ways 1) homes grouped by warmest to coolest ambient evening temperatures, and 2) homes grouped by whether there was installed central AC. We then analyzed the difference in building characteristics between the groupings, using variables available in the Home Energy Score database. Analysis of homes by binning temperatures into coolest areas to warmest areas (5 bins) showed that the areas in the city with the coolest evening ambient temperatures had the highest installed levels of air conditioning (68%) compared to the city-wide average (53%). When comparing this bin of homes to the rest of the sample, we found that homes in the coolest areas are newer, larger and use more total source energy (Welch's t p-value <.0001, Cohen's d medium effect size) compared to homes in areas with higher ambient heat. Two additional variables, Base EUI was found to be lower, and Energy Costs were found to be higher, with a small effect size. When looking at building characteristics in homes with and without air conditioning, we found that the largest effect of the variables tested is year built (Welch's t p-value <.0001, Cohen's d medium effect size), indicating that homes with AC are newer than homes without. We also found several variables to be statistically significant, with a small effect size (larger Home Size, smaller Base EUI, Afternoon and Evening Temperature). Finally, analysis of spatial autocorrelation using the Global Moran's I showed that the presence of air conditioning is not randomized, but clustered throughout the city (z-score 92.8, p-value <0.001) with greater numbers located in higher income areas. Results of grouping homes in two ways reveals a more sizable effect when looking at distributions of ambient temperature distributions.

Previous analysis of AC adoption indicates that household income is a determinant of whether AC is present in a home (Davis & Gertler, 2015; Goldsworthy & Poruschi, 2019; Ramos et al., 2021), and age and size of a home has traditionally been an indicator of energy use (Aksoezen et al., 2015; Frederiks et al., 2015). Further, heat-related mortality is highest for low-income residents partially due to the fact that low-income neighborhoods suffer from a lack of installed air conditioning (Ito, Lane, & Olson, 2018). The findings from this paper show that newer homes tend to be located in cooler, more affluent parts of the city, and these homes have higher rates of installed AC, they are larger and use more energy compared to homes in other areas with warmer ambient temperatures. These homes also have smaller EUI, even though they are consuming more total energy. Higher EUI is an indicator of increased energy poverty risk (Jessel et al., 2019; Reames, 2016b). The added risk presents further complexities when considering climate change mitigation strategies for low-income populations. For example, when considering interventions for extreme heat in low-income areas with high EUI, the building envelope should be tightened before adding mechanical equipment such as central AC, heat pumps or mini-split heat pumps to reduce the risk of increasing energy burdens while providing access to cooling for occupants.

Chapter 3 summary and conclusions

Wildfire trends throughout the world continue to increase. Climate change is a major culprit, increasing the potential for wildfires, especially large-scale, megafires (Barbero et al., 2015; Yongqiang Liu et al., 2010). In the Pacific Northwest, climate change is increasing outdoor particulate matter concentrations through extreme heat and wildfire events (Geiser & Neitlich, 2007). During wildfire events large amounts of woodsmoke is released that along with fine and ultra-fine particulate matter ($PM_{2.5}$), contain complex gaseous compounds that include nitrogen oxides, carbon monoxide, methane and hundreds of volatile organic compounds (VOCs) and oxygenated VOCs (OVOCs) (Jaffe et al., 2020). Prior studies have found that exposure to wildfire smoke increases mortality risk, respiratory illness, and cardiovascular mortality (Aguilera et al., 2021; Anjali et al., 2019; Johnston et al., 2011; Richardson et al., 2012). Like with other types of pollutant exposures, vulnerable populations such as children and the elderly have higher risks for illness (Holm et al., 2021). This Chapter used experimental data and modeling approaches to study the impacts that large wildfire events have on particulate concentrations ($PM_{2.5}$) inside homes. The indoor/outdoor ratio (I/O) was measured, controlled for building characteristics. The impact of high efficiency filtration and a portable air cleaner was also measured, along with a modeling exercise that measured performance based on previous study (Fisk & Chan, 2017).

The outdoor and indoor $PM_{2.5}$ concentrations were measured using a Clarity Node monitor from September 12-19, 2020. Concentrations throughout the study period were extremely high, with peak outdoor concentrations during this period reaching 717 ug/m^3

on September 13th, with a mean value of 277 ug/m^3 and a median value of 282 ug/m^3. The maximum indoor concentration reached 421 ug/m^3 also on September 13th with a mean value of 124 ug/m^3 and a median value of 110 ug/m^3 during the study period. In general, the interior concentrations were much lower than the exterior during the time frame studied but followed a similar trend as the outside air. The AQI reference levels for $PM_{2.5}$ concentrations according to the EPA are unhealthy (AQI 151-200): 65.5-150.4 ug/m^3, very unhealthy (AQI 201-300): 150.5-250.4 ug/m^3, and hazardous (301-500): 250.5-500.4 ug/m^3. Anything over AQI 500 (500.4 ug/m^3) is too high to be captured within the documented index (U.S. EPA, 2018).

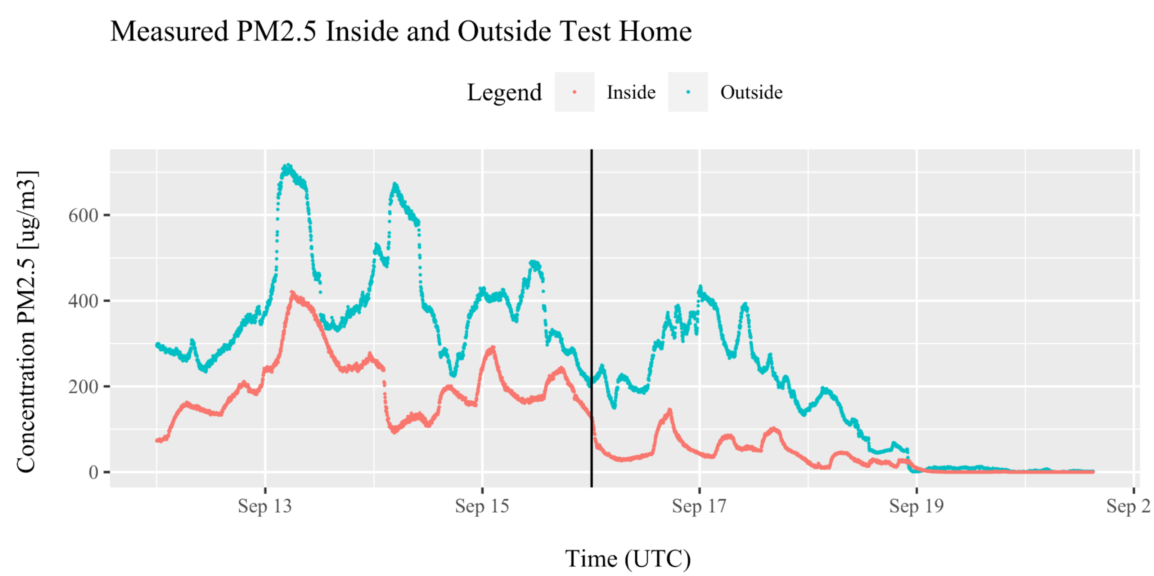

Figure 1. Raw $PM_{2.5}$ concentrations measured with the Clarity Node outdoors (blue) and indoors (red). Black vertical line indicates the time when the portable air cleaner was turned on.

Figure 2 presents the outdoor and indoor concentrations along with the model prediction for i3.5 (intermittent HVAC operation, high efficiency capture filter and portable air cleaner). The model predicted concentrations shown inside the home for the time period of the experimental conditions. The model predicted lower concentrations relative to the measured indoor concentrations for the first part of the experiment, but after the air cleaner was turned on beginning on September 16th, the model performed relatively well compared to measured concentrations.

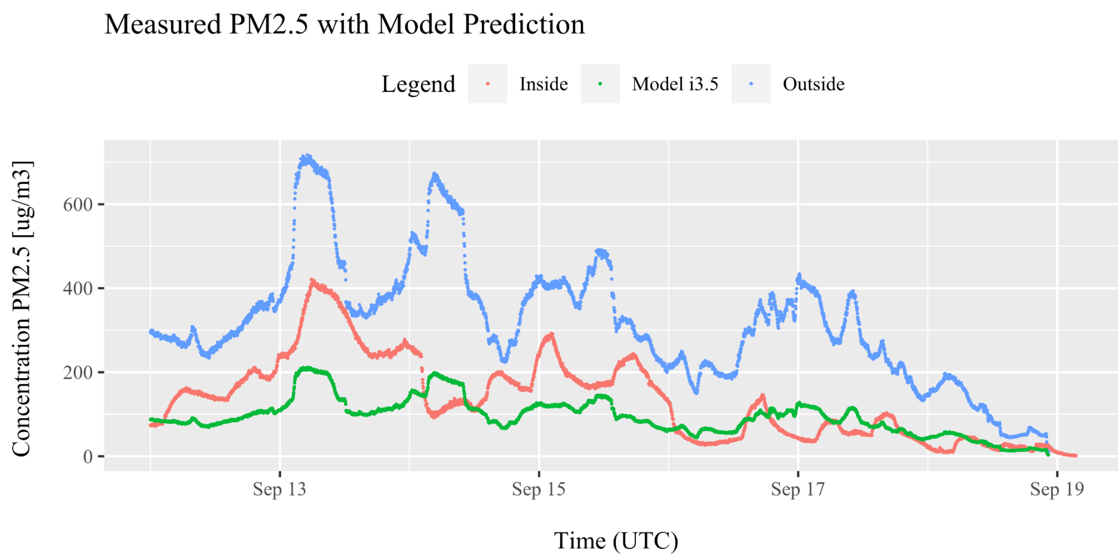

Figure 2. Raw $PM_{2.5}$ concentrations measured with the Clarity Node outdoors (blue) and indoors (red), with model i3.5 prediction indoors (green).

The Fisk & Chan model predicted a I/O ratio of 0.48 for condition i3 (high efficiency HVAC filter) and 0.24 for condition i3.5 (high efficiency HVAC filter + portable air cleaner). Measured results were 0.38 and 0.30, respectively. Model configuration i3 had a R2 value of 0.31, indicating the fit of the model to measured data should be improved. The i3.5 model performed well (R^2=0.88) using the average assumptions about building characteristics determined by Fisk and Chan (2017). Although the smoke concentrations during the experiment time frame were an order of magnitude higher (mean 124 μg/m^3) than those used during the model development (mean 56.9 μg/m^3), the reduction normalizations predicted the experimentally observed conditions fairly well. The model assumptions about performance of a high efficiency HVAC running intermittently (model condition i3) overpredicted the benefit of the upgraded HVAC filter in the system. It may be appropriate to further examine the assumptions for filtration performance in heavy smoke conditions like those observed during the experimental work.

The results of the study help inform future wildfire smoke modeling efforts by demonstrating that the model developed by Fisk and Chan (2017) is robust for estimating air quality in homes during wildfire events. The Fisk model assumptions are well documented and easily modified by other authors for large data sets. The building stock assumptions used are also adequate representations for our test home, resulting in relatively good approximations if no other information about the home and operation is known. That said, the $PM_{2.5}$ concentrations inside the test home were extremely high, even with intervention measures. One of the interventions was to run the HVAC system with a high MERV filter intermittently and the second intervention included the intermittent HVAC operation plus a portable HEPA air cleaner, finding both interventions to lower the concentrations of PM2.5 indoors, as noted by others in previous research (Barn et al., 2008; Xiang et al., 2021). However, both interventions will only be available to a home with installed AC (assuming the smoke event occurs in the summer cooling season) or with a central fan. Central AC systems are only present in about 50% of Portland homes, indicating this intervention is not available to many households. The levels of installed AC are also disproportionate relative to income, meaning that low-income households may not have access to this intervention strategy

(Davis, Gertler, Jarvis, & Wolfram, 2021). Additionally, the study found the second intervention (intermittent HVAC operation + portable air cleaner) to be effective, similar to previous research (Barn et al., 2008; Xiang et al., 2021).

Chapter 4 summary and conclusions

According to the U.S. Energy Information Administration's Residential Energy Consumption Survey (RECS), total energy expenditures in the United States are approximately $218 billion annually, an average of $1,900 per household (U.S. EIA, 2018b). The energy burden, defined as the percentage of income spent on energy resources varies dramatically depending on socio-economic strata. While the average U.S. urban household spends 3.5% of its income on energy, urban low-income and African American households spend 7.2 and 5.4% respectively (Graff & Carley, 2020), highlighting the chronic disparity between populations. The amount of consumption and expenditures is not trivial; previous analysis has found that low-income residents spend approximately $20 billion on energy expenditures per year, amounting to approximately 8.6% of residential energy use (Hernández & Bird, 2012). In the 2015 RECS, 37% of US households reported they experience energy insecurity and 25% reported reducing or forgoing medicine or food to pay for energy costs (U.S. EIA, 2018). This paper investigated the factors associated with building energy efficiency in low-income households and explored the ways that energy efficiency (or inefficiency) in homes impacts energy burdens. Using two novel, robust datasets, we ask the following questions: 1) what ways do housing characteristics affect the likelihood of energy burdens? 2) what are the disparities associated with housing characteristics between low-income homes and the general population? and 3) what is the potential for a double energy burden for low-income households?

To explore these questions, data from two energy labeling programs were compared. The first was Home Energy Score (HES) data from all homes in Portland, OR that were sold over the past 3 years (n=16,731). The second was HES data from a low-income retrofit program, aimed and enhancing efficiency of vulnerable households above Weatherization Assistance Program levels (n=107). A series of statistical tests were used to compare the two datasets, focused on individual measures that were inputs to the HES modeling tool, including home age, location, size, HVAC type/efficiency, energy costs, EUI, etc. A Welch's t statistic was calculated to look for a difference in mean values within the spread of the data. A Cohen's d was calculated to measure the effect size of the difference in standard deviations, to test for practical significance. We found statistically significant differences in home size (smaller in the low-income sample), EUI (higher in the low-income sample) and energy costs (lower in the low-income sample), and Cohen's d estimates were small, indicating the effect size between the two samples was rather low. Home age, number of bedrooms, total source energy use and CO_2 emissions were similar between samples. We found that more low-income homes use fuel oil for HVAC systems, indicating low-income households have older, inefficient, carbon intense equipment. Additionally, the median performance of HVAC systems was consistently lower in the low-income sample. The average energy burden of the low-income sample was 7%, reaching as high as 17%, compared to 3% for the general sample (p=<.0001, large effect size).

In combination, the findings and observations of this study highlight inequities in the energy performance in the low-income housing stock. Traditional technology diffusion of energy efficiency measures presents significant market failures associated with equity (Jaffe & Stavins, 1994). Efficient technology solutions are often not available to low-income households, forcing households in need to rely on Weatherization Assistance Programs or energy bill assistance. Both options do nothing to address and correct the fundamental issues of inefficient housing, which we are highlighting in this study by looking at individual building measures. When subsidies are available, the additional cost is still often out of reach for low-income households (Brown et al., 2020), and in areas with high poverty, households may pay a premium for energy efficient technologies, compared to wealthier neighborhoods (Reames, Reiner, & Stacey, 2018). Institutionally, many utility programs that subsidize technology access through ratepayer dollars end up financing wealthy neighborhoods to adopt technologies, using the capital gained from lower-income areas (Miller et al., 2015). When considering decarbonization and energy transitions, policy mechanisms that support energy equity by addressing market failures associated with technology transfer should be considered.

Observations across studies

Several themes emerged as primary observations across the three studies. First, fundamental conclusions from all three papers highlight the need for energy efficient, resilient housing. Energy efficiency is often thought of as air sealing and LED lighting. But the need for deep energy retrofits that go beyond simple fixes is necessary to mitigate climate change related exposures associated with extreme heat and wildfire. High-performance new homes, and deep energy retrofits in existing buildings can help ensure that resiliency infrastructure is created. Additionally, the building sector is a significant contributor to greenhouse gas emissions, and decarbonization is necessary to meet climate-related goals (Leibowicz et al., 2018). Decarbonization of the building sector is no small feat; buildings account for 40% of primary energy consumption, and fossil-fuel combustion in buildings leads to roughly 30% of total greenhouse gas emissions. Energy efficiency, electrification and smart technologies are fundamental strategies to reduce consumption and shift away from fossil-fuel use in buildings. Each paper in this dissertation highlighted the need for energy efficient, resilient housing, and found that the current state of housing in Portland Oregon needs significant retrofits in order to decarbonize.

Decarbonization requires a significant energy transition, a shift that requires broad-reaching changes to fundamental processes associated with energy production and consumption (Miller, Iles, & Jones, 2013). This energy transition carries significant societal risks unless the movement is carried out with equity and justice as a top priority. Low-income, vulnerable and communities of color have higher energy burdens compared to affluent populations (Lewis et al., 2020). Furthermore, systemic racism and historic exclusionary policies have resulted in increased risks (environmental, climatic, economic, and social) to low-income and communities of color (Schell et al., 2020), and underserved communities often do not have financial resources for, or access to, advanced building technologies (Reames et al., 2018). Each paper in this study highlighted the need for equitable distribution of energy-saving resources and technologies. As we move towards decarbonizing, resiliency and technology access in buildings is a fundamental need and ensuring technology diffusion from the bottom-up as opposed to the top-down is an opportunity that carries both environmental and social benefits.

The time and expense associated with conducting deep energy retrofits at scale throughout the United States is a significant barrier to advancing energy performance and resiliency in the residential sector. There are insights from this research that a broad range of stakeholders and decision makers can consider while forming policy to advance a decarbonized, resilient housing stock. The first is to develop incentives and programs that promote deep energy retrofits in low-income housing recognizing that these efforts will go beyond saving energy to provide thermal protection during extreme heat and help keep indoor environments safer during wildfire events. The second is to develop approaches grounded in building science to address exposure vulnerability in housing. This means a systems-thinking approach to keeping occupants safe, that incorporates not only technology access, such as air conditioning installations, but also approaches to increase efficiency of the thermal enclosure to allow for the low energy loads. For example, the Energiesprong program, which started in the Netherlands and has expanded to the UK, France and Germany takes a systems-design approach to building retrofits, combining façade and mechanical upgrades to produce net-zero energy homes[5]. The program is funded by a mechanism developed by regulators and banks to offset upfront costs with estimated cost savings over a period of 30 years, which shifts the cost of

[5] https://energiesprong.org/

energy to a service-based model. These service-based models are good springboard approaches to use for retrofitting the United States housing stock, and should be considered to advance energy, resiliency and equity efforts.

Limitations of the research and future work

There are several limiting factors associated with this research that is worthwhile to discuss in depth. First, the study area only included Portland, Oregon, and while some similar observations can likely be made in other areas, the dynamics present in this study area might not transfer to other regions. Future study could compare and contrast the urban dynamics associated with Portland, Oregon and another study area to draw more substantial conclusions. Specific limitations are discussed in depth for each chapter below.

<u>Limitations to Home Energy Score analyses (Chapters 2 and 4)</u>

Both Chapter 2 and 4 used the Home Energy Score data, which has some limitations. Although extremely robust, the Home Energy Score database outputs associated with energy costs, energy use intensity, carbon emissions, and total source energy consumption are modeled results based on the individual inputs that are used to generate a score. The use of modeled results has some limitations, primarily associated with the reliance on energy models (HES uses DOE E+) to derive results that might have more nuanced factors associated with the results. To calculate energy burdens in Chapter 4, the full HES sample relied on Census Median Household Income (MHI) data, which is reported at the Census Block Group (CBG). In any given CBG, there could be as many as

40 homes, so assuming they all have a single MHI is unrealistic. Future study might consider survey development to add granularity to Census MHI. Additionally, only a percentage of the low-income sample provided their MHI data. The subset was used for demographic and energy burden analysis.

Limitations to IAQ experiment and modeling (Chapter 3)

The equipment, calibration, set up and data monitoring of a building to measure IAQ is expensive and complex. I was fortunate to have access to equipment from the Pacific Northwest National Laboratory and Portland State University. However, cost and effort limit the ability to instrument many homes, and this research was conducted based on instrumentation of only one house. In addition, the infiltration rate was derived from the results of a blower door and modeled using an infiltration model developed at the Lawrence Berkeley National Laboratory. More precise methods are available to measure air exchange but were not used in this study.

Additionally, the study applied the experimental data as inputs to a model that estimated impacts of wildfire on a broader scale. The measured data only included one home. To determine city-scale performance of the housing stock, data from more individual homes is needed. The model developed by Fisk and Chan (2017) looked at both IAQ and health impacts from wildfire smoke. This study only investigated the IAQ exposure impacts and the potential decreases possible with two interventions. Broader health implications were not investigated.

Opportunities for future research

Each paper presented in this dissertation focused on singular analyses associated with heat and wildfire pollutant exposure and building energy equity. Future research could model how different climate chance scenarios would impact the observations made here, with emphasis on how individual impacts of climate chance might alter the results realized today. This analysis would broaden the study of this dissertation and might be a helpful way to extrapolate out findings from the Portland, Oregon study area to other regions in the United States, or abroad.

The IAQ analysis in Chapter 3 provides some of the basis for looking at city-scale impacts of extreme smoke events caused by wildfire. The HES database includes many homes with blower door data, and the volume of the home can be calculated based on reported square footage and ceiling height. These two datapoints would allow general approximations of infiltration to be modeled and applied to experimental data gathered during the smoke event in 2020. Using the augmented model developed by Fisk and Chan, regional characterization of IAQ based on home vintage or "leakiness" could be estimated. Further, epidemiological data could be added to estimate the health impacts associated with exposures based on modeled and experimental results.

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