DISSERTATION

SYSTEMS-BASED APPROACHES FOR EVALUATING RESIDENTIAL-BASED HAZARDS TO INFORM ENVIRONMENTAL EXPOSURE INTERVENTION DESIGN

Submitted by

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ABSTRACT

SYSTEMS-BASED APPROACHES FOR EVALUATING RESIDENTIAL-BASED HAZARDS TO INFORM ENVIRONMENTAL EXPOSURE INTERVENTION DESIGN

Housing is an essential aspect of the physical built environment, where people spend most of their time, and a key determinant of health. Sub-standard and poor physical housing conditions (e.g., disrepair, deferred maintenance, and deteriorated physical environment) and exposures of inhabitants to lead, pests, air pollutants, and other indoor contaminants are associated with a wide range of health conditions, including respiratory infections, asthma, lead poisoning, injuries, chronic disease outcomes (e.g., cardiopulmonary conditions) and mental health illness. The environmental justice (EJ) research community that has focused on residential exposures has documented that adverse environmental exposures associated with residential settings and built environments are unevenly distributed and often disproportionately affect low-income and socioeconomically disadvantaged populations in the United States. Hence, work remains to be done if we intend to develop and maintain healthy residential environments for vulnerable population groups. However, a central challenge to this effort is the complex system of sources and source activities that contribute to and drive residential exposures, which makes it difficult to identify and isolate dominant sources.

This dissertation sought to holistically investigate sources of three prevalent home-based exposures in the United States – i.e., flooding, lead, and indoor chemical mixtures. Through a combination of empirically-based and modeling approaches, this work brought together information on physical dwellings, their conditions and surroundings, the overlying sociodemographic characteristics of the people living in them, and the behaviors and activities that people undertake in their homes. The central hypothesis of this work has been that this approach would improve the identification of sources and their relative contributions to exposures in the residential environment. Significant findings from this work include: (i) socioeconomically disadvantaged populations in all three studies tended to have higher environmental exposures, regardless of exposure type, including natural hazards (i.e., floods), legacy pollution (i.e., lead), and pollutants driven by daily human activity (indoor air pollutants of outdoor origin); (ii) sources of environmental exposures varied within the same study and, at times, were more subtle than initially hypothesized in the literature, suggesting that the more holistic approaches taken in this work have practical value; and (iii) residential interventions to reduce adverse exposures could provide some measurable benefits to residents if customized to local occupants' needs in solving more building-related problems and providing higher residential satisfaction. In two of the three studies, we have worked closely or directly with the communities from which the data are collected. Thus, we expect outputs from this work to improve the design and delivery of home-based interventions for adverse environmental exposures through direct engagement with local decision-makers and more traditional scholarly communication channels.

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A big thank you to the SWISCHEESE team and EPA for providing the funds for research. To my graduate colleagues, Collin, Andrew, Jorge, you have been a great supporting cast. "*It is not about the numbers but the quality.*" You guys rock!

Finally, to GOD eternal, whose special grace, mercy, love, and favor have brought me this far. My success shall sing praise to thee and not be silent. Therefore, I shall return to HIM all the glory, honor, dominion, adoration, and praise. Amen!

DEDICATION

This dissertation is dedicated to the Almighty God, the giver of life and the source of wisdom that produced this document and completed the degree program.

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CHAPTER ONE: INTRODUCTION

1.0. Introduction

The physical structures where humans live and work collectively, including homes, buildings, transportation systems, open spaces, urban spaces, walkways, roads, parks, and infrastructure, comprise the built environment (Frank & Engelke, 2005). There has been a growing understanding of the role numerous environmental exposures related to the built environment plays in physical and mental health (Brown et al., 2009; Titze et al., 2010; Villanueva et al., 2013). Specific environmental exposures in the physical built environment associated with adverse health outcomes are enormous. Several examples include residents' proximity to roadways associated with exposure to traffic-related air pollution, lead (Pb), smoke, artificial light at night, overcrowding, and noise (Gascon, Vrijheid, & Nieuwenhuijsen, 2016; Giles-Corti et al., 2016; Franklin et al., 2020). In addition, exposures to systems and structures in the environment that support healthy behaviors (e.g., grocery stores, recreational opportunities, medical care, transportation); and community design (e.g., parks, football fields, resident's accessibility to goods and services) (Sallis et al., 2009; Perdue et al., 2003; Srinivasan et al., 2003) have been associated with beneficial health outcomes.

A significant number of studies have identified and evaluated the effects of specific exposures assessed in the physical built environment on a range of human health endpoints and outcomes (Cummins & Jackson, 2001; Ding & Gebel, 2012; Malambo et al., 2016; Nguyen et al., 2016; Perdue et al., 2003; Peters & Pope, 2002; Tulve et al., 2016). Exposures to structures and features of the built environment have been used as surrogates for exposure to hazards associated with those features and adverse or (beneficial) health outcomes. For example, residential proximity to highways is a common proxy measure of air pollution exposures to fine particulate matter (i.e., $PM_{2.5}$, particles that are 2.5 microns or less in diameter) from vehicular traffic. The resulting adverse health outcomes associated with $PM_{2.5}$ exposures include asthma, cardiovascular and respiratory disease, and morbidity (Hales et al., 2013; Carey et al., 2013; Cesaroni et al., 2013; Lepeule et al., 2012; Perlin et al., 2001). As another example, the age of housing is an exposure metric in the residential built environment frequently used as a surrogate for exposure to lead (Pb) in homes. Lead in residential homes is associated with detrimental neurodevelopmental and cognitive outcomes amongst children under five years old (Bellinger, Needleman, & Eden, 2003; Bellinger, Stiles, & Needleman, 1993)

Housing is an essential aspect of the physical built environment, where people spend most of their time, and a key determinant of health (Dunn et al., 2006; Howden-Chapman, 2003; Krieger & Higgins, 2002). Housing represents a place of various adverse exposures, as many features and conditions of one's home can have direct or indirect impacts on health (Jacobs, 2011). The physical condition of the home, including the integrity of the structure; the systems that govern heating, cooling, and ventilation; internal conditions such as damp, cold, and indoor contamination and the (voluntary or involuntary) management of these conditions; and the behavior of the occupants all have potential to impact health (Jacobs, 2011). In addition, sub-standard and poor physical housing conditions (e.g., disrepair and deteriorated physical environment) and exposures of inhabitants to lead, pests, air pollutants, and contaminants are associated with a wide range of health conditions, including respiratory infections, asthma, lead poisoning, injuries, and mental health (Sharfstein et al., 2001; Krieger & Higgins, 2002; Rauh et al., 2008).

The environmental justice (EJ) research community focusing on residential exposures have documented that adverse environmental exposures associated with residential settings and built environments are unevenly distributed and often disproportionately affect low-income and socioeconomically disadvantaged populations in the United States (Morello-Frosch & Lopez, 2006; Srinivasan et al., 2003; Bashir, 2001). Socially and economically marginalized populations have unequal opportunities, social connection, and power for self-protection, prevention, and mitigation of adverse environmental exposures; and they are mainly affected in terms of morbidity and mortality (Chakraborty et al., 2014; Grineski et al., 2014; Montgomery & Chakraborty, 2015). However, despite the scientific progress in understanding the connection between housing conditions and health, most research on housing and health still addresses a narrow range of housing conditions, potential health exposures, and associated health concerns (Swope & Hernández, 2019).

Only recently has the scientific community begun to investigate the association between residential exposures and human health as a complex interaction between building occupants (who they are and what they do), neighborhood conditions, and an array of physical and socioeconomic factors. Nevertheless, our understanding of how residential environmental exposures vary in the United States with housing type (single-family, multi-family, and mobile homes), housing tenure (owner or renter-occupancy), and public housing units is still limited.

Given the complexity of how socioeconomic status and occupant's decisions could influence residential health outcomes, the introduction of adequate interventions to mitigate the harmful residential exposures without examining the interactions of socioeconomic status, physical housing characteristics (e.g., the structure, condition, and age of housing), housing types and tenure, and the neighborhood characteristics will be very challenging. In addition, it is also essential to consider how these variables mentioned above are spatially distributed within the neighborhood scale (e.g., block groups or census tracts). Thus, the neighborhood scale reveals geographic patterns of potential population vulnerability to disasters and harmful environmental pollutants to better understand mitigation, preparedness, response, and recovery (Morrow, 1999; Smiley, 2020).

Significant advances such as physical home improvements, setting guidelines, regulatory actions, and monitoring efforts have been in place to protect people and properties from known housing hazards. For example, the ban on lead-based paints in residential homes has helped reduce childhood lead poisoning (Dignam et al., 2019). In addition, housing intervention research indicates that physical improvements in housing generally lead to positive health effects, especially those related to warmth and energy efficiency, consistently improving general health, respiratory health, and mental health (Howden-Chapman, 2003). Despite the substantive efforts and advances to reduce the risks, knowledge gaps that prevent the efficient implementation of protective strategies still exist due to a disproportionate emphasis on physical housing improvements and quality as a singular approach, a limited system of reducing residential exposures. The physical improvements in housing could increase their impact if they expand or diversify to take a more systems-oriented, population-scale, and adaptive approach that includes accounting for human behaviors and actions contributing to residential and environmental exposures. This dissertation investigates three systems-based approaches to evaluating home-based hazards to improve home-based interventions' design and delivery against known, pernicious, adverse environmental exposures.

1.1. The overall goal of the research study

The overall goal of this dissertation is to improve how residential environmental exposures are integrated into more extensive studies of relationships between the built environment and health affecting residential housing in the United States. The research efforts will provide a robust basis for policy development, resilience planning, and sustainability of residential housing and ensure equitable management of the environmental risks. The dissertation will focus on three specific challenges facing residential housing in the United States, including (i) the spatial distribution of socioeconomically disadvantaged groups, housing types, and housing tenure risk factors associated with different flooding types; (ii) lead (Pb) exposure in homes causing pediatric lead poisoning; (iii) poor indoor environmental quality (IEQ) in low-income housing units.

This dissertation contains a collection of manuscripts that have been drafted or submitted for publication in refereed journals.

(a) Spatial distribution of sociodemographic and housing-based health risk factors and their relationships to flooding hazards in the U.S.
(b) Investigating patterns and sources of variability in children’s blood lead levels in Milwaukee County using machine learning models

(c) Evaluating baseline patterns of indoor environmental exposures and their determinants in pubic housing.

1.2. Outline of the dissertation

Chapter one is the introduction to this dissertation. The chapter introduces the research, the background, problem statement, objectives, and the project framework within which this dissertation is conducted.

Chapter two is the literature review. This chapter provides a detailed review of the literature, definitions, concepts, and methods relevant to the three abovementioned specific challenges facing residential housing examined in this dissertation. The literature review is divided into three sections. Each section focuses on reviewing the current state of the literature on the topic, the challenges and limitations, and this study's contribution to improving and bridging existing literature gaps.

Chapter three investigates the extent to which different sociodemographics (e.g., socioeconomically disadvantaged groups), housing types, and housing tenure are subjected to risks associated with specific flood types in the contiguous U.S.

Chapter four examines the patterns and sources of variability in children's blood lead levels in Milwaukee County using machine learning models. The study examines the relative contributions of different sources of lead exposure and how their environmental exposure profiles interact synergistically to produce comparatively higher blood lead levels (BLL) outcomes for children in multiple exposures in Milwaukee County.

Chapter five identifies the sources of indoor and outdoor concentrations of particle and gas-phase pollutants in occupied and unoccupied low-income Denver Housing Authority (DHA) residential complexes in Denver. It further establishes baseline conditions in public housing, slated for redevelopment, to support future longitudinal analyses of changes in housing quality, indoor air quality, and ultimately exposure and health outcomes associated with significant, wholesale replacement of housing.

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CHAPTER TWO: LITERATURE REVIEW

PROJECT A: SPATIAL DISTRIBUTIONS OF SOCIODEMOGRAPHIC AND HOUSING-BASED HEALTH RISK FACTORS AND THEIR RELATIONSHIPS TO FLOODING HAZARDS IN THE U.S.

2.1. Introduction

Flooding is the most significant natural hazard affecting several millions of people globally each year (Jonkman, 2005). Several decades ago, flood events that caused significant disruption and incapacitated societies by causing high mortality rates and costly damages were commonly associated with developing countries (Wisner et al., 2004). However, wealthy countries have been experiencing the most extensive, damaging, and costly floods in recent decades. For example, from 1980 to 2020, the United States experienced an 11% increase in the frequency of flooding, including coastal and inland flooding, causing an average of $330.5bn in damages (NCEI, 2021). Thus, flooding is the costliest natural disaster in the United States, contributing to national burdens on social, economic, and health systems (Walker, 2012).

Scientific evidence suggests that the frequency, severity, and distribution of flood hazards will increase in the future due to a combination of factors, including intensifying developments in areas subject to flooding, changing storm and precipitation patterns, and sea-level rise (Allen and Ingram, 2002; Kirtman et al., 2013; Prein et al., 2017). Moreover, the populations and assets exposed to floods have increased more rapidly than overall population or economic growth (Bouwer et al., 2007, Di Baldassare et al., 2010, Bouwer, 2011, Jongman et al., 2012; Kundzewicz et al., 2014). While the understanding of flood mapping showing coverage of population and property values in proximity to floodplains has dramatically improved over the years, the knowledge of flood hazard, exposure, and vulnerability remains one of the biggest challenges in flood risk assessment to date (Mechler and Bouwer, 2015; Visser et al., 2014). Thus, it is essential to understand who and where across the contiguous United States (CONUS) are most vulnerable to different flooding types to help inform how appropriate pre-and post-flood mitigation efforts can be implemented.

2.2. Classification of floods

Floods are caused by the combination of complex hydrologic, geomorphologic, climatic systems, and notably precipitation (intensity, duration, amount, and phase) (Bates et al., 2008; Dougherty and Rasmussen, 2019; Agel et al., 2019). Flooding is classified into three main categories: Flash flooding, river flooding, and coastal flooding (French and Hot, 1989). Flash flooding is defined as “a flood that rises and falls quite rapidly, usually as a result of intense rainfall over a small catchment area (usually less than 1000km^2), in a short amount of time, usually under 6 hours (Calianno et al., 2013; Llasat et al., 2016). River flooding is defined as “the rise of a river to an elevation such that the river overflows its natural banks causing or threatening damages,” and coastal flooding occurs from “storms where water is driven onto land from an adjacent body of water.”

2.3. Environmental injustice associated with flood risks.

Flood risk reflects the intersection of three spatial distributions: the flood hazard, the exposed population, and their underlying vulnerability to flooding hazards (Kron, 2005). While our knowledge of hazard and exposure has significantly improved over the last decade, vulnerability remains challenging in flood risk assessment to date (Koks et al., 2014). The devastating outcome of Hurricane Katrina in 2005 and the governmental failure in response to the disaster prompted academic researchers and activists to consider social injustices associated with floods (Chakraborty et al., 2014). More specifically, the alarming unequal impacts of Katrina on communities of color (e.g., African-American) and low-income residents in the City of New Orleans inspired subsequent empirical research on flooding and environmental justice (Dixon and Ramutsindela, 2006; Ueland and Warf, 2006; Colten, 2007; Bullard and Wright, 2009; Walker and Burningham, 2011).

Environmental injustice is defined broadly as “the unequal distribution of environmental risks and benefits” (Chakraborty and Green, 2014). The burden of the risks and dearth of the benefits falls primarily on racial minorities, lower-income populations, and other socially vulnerable individuals (Chakraborty et al., 2014). Thus, the first step for analyzing the environmental justice implications of flooding is to determine who is living at risk of flooding or the social characteristics of persons living in proximity to coastlines, rivers, and water bodies. Several studies have examined the inequities associated with the aftermath of flood events, including physical and psychological impacts, response, recovery, and rebuilding (Elliott and Pais, 2006; Morse, 2008; Zahran et al., 2008). Other studies have investigated a pre-flood approach to document the populations (e.g., racial groups, socioeconomic attributes) potentially affected during flood events (Fielding and Burningham, 2005; Walker et al., 2006; Ueland and Warf, 2006; Johnson et al., 2007; Maantay and Maroko, 2009). Collectively, these studies concluded that socially disadvantaged or marginalized groups have higher exposure to flooding risks than socially advantaged people (i.e., those of low social vulnerability).

Chakraborty et al. (2014) expressed a critical limitation to these previous environmental justice studies stating "*all flood-prone areas have been assumed to pose an equal risk to residents and thus treated as one aggregate risk zone.*" Meanwhile, the socioeconomic characteristics of people exposed to flood risk can vary widely. Moreover, the approach used in these studies failed to consider particular factors such as differences in frequency and probability of flood events, disparities between coastal and inland flood risk zones, and locational benefits (e.g., employment opportunities, proximity to schools, or other social amenities). For example, studies that considered the effect of residential locations (Bin and Kruse, 2006; Ueland and Warf, 2006; Montgomery and Chakraborty, 2013) suggest that socially advantaged people (i.e., affluent and middle class) are more likely to have higher exposure to floods in coastal flood-prone areas. The higher exposure is because they tend to live in higher-valued coastal and waterfront properties associated with environmental amenities such as ocean views and proximity to beaches (Chakraborty et al., 2014; Fielding and Burningham, 2005; Grineski et al., 2013; Montgomery and Chakraborty, 2013; Ueland and Warf, 2006).

However, a similar exposure pattern was not observed in the inland flood areas. The exposed socially disadvantaged groups in the inland areas lack the resources to protect themselves pre-event, evacuating in response to flooding, accessing social protection resources to reduce flood impacts such as insurance, and lastly, difficulties in post-flood recovery and assistance (Pelling, 1999; Mustafa, 2005; Elliot and Pais, 2006; Collins 2009, 2010; Maldonado et al., 2016). In addition, several studies indicated that socioeconomically disadvantaged groups experience higher mortality and morbidity during flood events (Collins 2009, 2010; Elliott and Pais, 2006; Maldonado et al., 2016; Mustafa 2005; Pelling 1999). The contrasting results from these studies support Chakraborty's argument that aggregating all flood-prone areas to pose an equal risk is misleading because people are not vulnerable to floods equally, and their levels of vulnerability differ.

Furthermore, most of the studies examining social vulnerability used the common key characteristics for clarifying variations in natural disaster impacts, such as class, race, income, ethnicity, gender, age, disability, health status, and immigration and citizenship status (Cutter et al., 2003, 2012; Wisner et al., 2004; Phillips et al., 2012; Chakraborty et al., 2014). For example, on race, studies (e.g., Chakraborty et al., 2014, Maldonado et al., 2016) investigated the social and spatial inequities in exposure to flood risks in Miami, Florida. The studies reported that non-Hispanic Black and Hispanic residents are significantly overrepresented in inland flood zones. At the same time, they are underrepresented in coastal flood zones characterized by affluence and higher income and housing values. On income, more low per capita income clusters and high ratios of economically disadvantaged people are located in the inland areas (Wing et al., 2019).

The spatial pattern that shows the minorities and low-income earners are overrepresented in the inland flood zones while the economically advantaged people are at most risk in the coastal flood zones has been increasingly important in the risk assessment of environmental hazards and also changed researchers' notion of *vulnerability*. Recently, Collins et al. (2018) argued that the affluent living in the coastal area as being socially vulnerable has two main limitations when conceptualizing environmental justice in the context of flood hazards. First, the distributive environmental justice literature is based on an incomplete conception of risk as high hazard exposure, which neglects people's capacities to reduce risks. For instance, socially elite residents may voluntarily expose themselves to flood hazards to pursue environmental amenities. They can often reduce the risks by harnessing a disproportionate share of the flood mitigation resources redistributed by state and market institutions to support flood preparedness, response, recovery, and reconstruction (Collins, 2010).

In addition, the risks of dwelling within coastal zones are offset by institutionally mediated access to mitigation resources, including flood insurance policies with premiums that are lower than the actuarial costs of flood risks (Collins et al., 2018). Therefore, a "procedural approach," defined as an environmental justice perspective that centers on residents' unequal abilities and differential capacities to mitigate flood hazards, should also be considered while examining the social vulnerability associated with floods. Second, the assumption that people select home locations to avoid hazards and not consider other associated residential benefits is misleading. While selecting their residential neighborhood, people consider locational benefits such as employment opportunities, accessibility, and amenities in distributing risks across different social groups (Boone, 2002; Oakes et al., 1996; Pelling, 1999; Wisner et al., 2004).

The lesson learned from the distributive and procedural approach of examining social vulnerability to floods reflects both positive and negative attributes necessary for researchers to examine the EJ implications of both flood hazards and water-based benefits. In addition, the integration of distributive and procedural approaches has continued to enlighten our comprehension of environmental injustices in the context of flood hazards and other unevenly distributed environmental risks and resources. Furthermore, the quantitative environmental justice analyses of aggregated sociodemographic data at different levels (e.g., census block groups, census tracts, and county) needs to focus on people's choices on the costs and benefits associated with flood-prone areas in order to characterize the environmental injustices they experience (Collins et al., 2018). Finally, given the complex environmental justice implications of flooding, there is a need for environmental justice scholars to examine how social vulnerabilities and other indicators such as housing types and tenure are subjected to different flood types, especially across the United States.

2.4. Flood risks associated with housing types and tenure

Few works have focused attention on the impact of flooding on housing types and tenure compared to physical vulnerability and social factors. However, the characteristics of renters are similar with aspects of social and physical vulnerability (Morrow, 1999), including being low-income earners, minorities, living in low-quality housing (Kreimer 1980; Morrow 1999; Peacock, Dash, and Zhang 2007), and lacking or limited control of resources (Van Zandt et al., 2012). In contrast, homeowners have access to funds, resources, and policies that allow them to prepare, anticipate, respond, and recover from disasters (Lee and Van Zandt, 2019). As a result, renters are also associated with higher displacement risks after a disaster (Rohe, Van Zandt, and McCarthy 2001; Burby, Steinberg, and Basolo 2003; Lee and Zandt, 2019).

Furthermore, rental housing is more likely to be older, poorly built, lack sanitation, located in areas vulnerable to flooding, and inadequately maintained than owners' housing (Morrow, 1999). Therefore, housing tenure characterizes the relationship between social and physical vulnerability because it captures the connection between the household and the housing unit. Thus, we might expect that housing tenure should be a mitigating (owning) or exacerbating (renting) influence on vulnerability (Lee and Van Zandt, 2019). In addition, renter-occupied single-family housing and other housing types more common to renters (e.g., duplexes and multifamily housing) were more likely to experience greater levels of damage and were slower to recover after a disaster (Peacock et al., 2014; Zhang and Peacock, 2010). While research studies have extensively informed us of the social vulnerabilities associated with flood, housing tenure and types have rarely been considered in the flooding and environmental justice literature. An important goal is to examine whether the spatial patterns and associations are consistent with different flood types. Therefore, this study aims to investigate to what extent are social vulnerabilities, housing types, and tenure associated with flood risks associated with different flood types.

2.5. Flood risks associated with different flood types

Of the three main types of floods mentioned in section 2.2, flood risk researchers have examined social vulnerabilities (e.g., Khadejei et al. 2020, Terti et al., 2017; Alipour et al., 2020); mortalities and morbidities (Ashley and Ashley, 2008; Ahmadalipour & Moradkhani, 2019) associated with flash floods more than those focusing on coastal and river floods. One possible reason is that flash flood events can be distinguished from riverine floods by their fast response to rainfall (Jonkman 2005; Gourley et al., 2013). For instance, previous studies have employed numerous data assimilation and statistical methods to assess the following: flash flood forecasting skills (Braud et al., 2018; Douinot et al., 2016; Edouard et al., 2018); investigate the impact of climate or land-use change on flash flood hazard (Jodar-Abellan et al., 2019; Kermanshah et al., 2017); develop indices to quantify flash flood hazard (Schroeder et al., 2016; Smith, 2010; Tincu et al., 2018); understanding social perceptions of flash flood hazard and risk (Bodoque et al., 2019; Lazrus et al., 2016; Lutoff et al., 2016); and characterizing flash flood patterns and regimes (Archer and Fowler, 2018; Marchi et al., 2018; Spitalar et al., 2014).

In addition, Alipour and Moradkhani (2019) provided a comprehensive analysis of flash floods across the CONUS that characterizes the attributes of flash floods, including duration, frequency, and associated impacts such as human injuries and fatalities. However, fewer studies compared similar characteristics with other flood types. Interestingly, Dougherty and Rasmussen (2019) provided the characteristics of two different floods (flash and slow-rise floods) across the CONUS to identify which regions are most vulnerable to specific floods in different seasons of the year. The study showed that different regions of the CONUS are exposed to varying amounts of flood episodes and rainfall accumulation, causing flash and slow-rise floods across the CONUS. Therefore, there is a possibility that the extent of social vulnerabilities, housing types, and tenure associated with flash and slow-rise floods would differ. Thus, our idea is to understand the environmental injustice associated with different flood types across the CONUS.

This study in chapter 3 relied on work by Dougherty and Rasmussen (2019), who created a flood-producing storm database by merging storm reports with streamflow-indicated floods. Here, we used the knowledge gained from the classification of flood types into slow-rise and flash floods across the CONUS to evaluate whether we can better understand environmental injustice by examining social vulnerability, housing types, and tenure associated with different flood types across the CONUS.

2.6. Contribution of this dissertation to the literature

The underlying evidence from the environmental justice literature suggests that socioeconomically disadvantaged populations tend to experience greater exposure to flooding risks than socially advantaged populations (i.e., those of low social vulnerability) in both pre-and post-event hazard exposures. However, other studies have reported that socioeconomically advantaged populations experience greater exposure to flooding risks (Collins et al., 2018). Moreover, some studies did not reveal clear patterns of disproportionate exposure for socially disadvantaged populations (Masozera et al., 2007; Masozera et al., 2017). Thus, understanding the patterns of social vulnerability associated with unique characteristics of a specific flood type could bridge the literature gap and improve the development and implementation of future guidance to reach those most in need and support equity changes in flood mitigation policy.

The study synthesized spatial information across multiple domains, including hydrologic, atmospheric, socioeconomic, and demographic disciplines, to examine the following questions: (i) To what extent are socioeconomically disadvantaged populations more or less vulnerable during flash or slow-rise floods? (ii) To what extent are housing types and tenure (i.e., renter- vs. owner-occupied housing) associated with greater exposure to flash or slow-rise floods?

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PROJECT B: INVESTIGATING PATTERNS AND SOURCES OF VARIABILITY IN CHILDREN'S BLOOD LEAD LEVELS IN MILWAUKEE COUNTY USING A MACHINE LEARNING MODEL.

2.8. Introduction

Despite removing lead from gasoline and paints, childhood lead poisoning remains a persistent environmental public health concern in the United States. BLL exceeding 5 μg/dL indicate lead poisoning, as defined by the Centers for Disease Control and Prevention (CDC). Nonetheless, no safe BLL in children has been identified. The existing literature on risk factors for lead exposure in children is extensive. However, it focuses primarily on elevated blood lead levels (eBLLs), defined as 5.0 μg/dL or more (to convert to micromoles per liter, multiply by 0.0483). Scientific evidence and literature revealed that even low BLL detectable at > 1.0 μg/dL in children could cause significant harm to the physical and mental health, neurological damage, reduced intelligence quotient (I.Q.), and developmental delays (Canfield et al., 2003; Nigg et al., 2010; Hauptman et al., 2017; Christensen et al., 2019; Lanphear et al., 2000; Sanders et al., 2009; Grandjean and Landrigan, 2014; Yeter et al., 2020; Hauptman et al., 2021).

Hauptman et al. (2021) reported a cross-sectional, retrospective study (between October 1, 2018 – February 29, 2020) that revealed individual- and community-level factors associated with detectable and eBLLs in U.S. children from a national clinical laboratory. The study showed that out of the 1.14 million children younger than six years living in all 50 U.S. states tested for blood lead levels, about 576,092 (50.5%) had detectable BLLs, with 1.9% having *elevated* BLLs of 5.0 μg/dL or more. The highest proportions of children with *detectable* BLLs were found in Nebraska (83%), Missouri (82%), Michigan (78%), Iowa (76%), and Utah (73%). In addition, six states had proportions of *elevated* BLLs more than double the national rate of 1.9%: Nebraska (6.0%), Ohio (5.2%), Pennsylvania (5.0%), Missouri (4.5%), Michigan (4.5%), and Wisconsin (4.3%).

2.9. Primary Sources of Lead in the Environment and Pathways of Exposure

Sources of early childhood lead exposure in the United States include lead paint in housing built before 1978 (Jacobs et al., 2002; Cantor et al., 2019); contaminated drinking water from the deterioration of leaded household service lines (Hanna-Attisha et al., 2016); house dust; contaminated soil (Mielke et al., 2016; Laidlaw et al., 2016; Ceballos et al., 2016; Entwistle et al., 2019); some consumer products; and lead-emitting industrial emissions (Gallons et al., 2006). In the last four decades, BLLs in children have decreased because of the government's successful policies to reduce Pb in the environment and banned lead-based paints in residential homes in 1978.

However, many U.S. children still live in homes built before lead-based paints in residential homes (Whitehead and Buchanan, 2019). Therefore, the deterioration of lead-based painted surfaces could result in loose particles being ingested or inhaled as dust by children (Gleason et al., 2019). Statistics show that among the approximately 24 million housing units in the United States that have deteriorated lead-based paint and high levels of lead-contaminated house dust, more than 4 million are homes to 1 or more young children aged 1 to 5 years (https://www.cdc.gov/nceh/lead/prevention/sources/paint.htm).

A few studies have shown an association between lead in water and blood lead levels in children (e.g., Brown and Margolis, 2012; CDC, 2004; Edwards et al., 2009; Triantafyllidou and Edwards, 2012). For example, Triantafyllidou and Edwards (2012) identified a positive relationship between drinking water lead levels and increasing BLLs while investigating the individual-level exposures of lead in water. Lead enters the drinking water through the lead-containing plumbing pipes. In the United States, lead pipes were used to construct water-main service lines in the late 1800s and early 1900s because of their pliability and resistance to corrosion compared to iron and steel (Lassovsky and Cohen, 1992). In 1991, the EPA estimated that about 20% (10.2 million) of all public water supply systems had lead service connection lines (USEPA, 2016). About 6.1 million lead-containing service lines still exist across the United States (Cornwell et al., 2016).

One of the efforts of the U.S. government to combat the lead exposure via lead pipe service lines supplying water into U.S. homes was the initiation of the lead and copper rule in 1991, which was part of the Safe Drinking Water Act. The rule initially required the replacement of the public and private water service pipelines. However, in 2000, the revised rule required only partial replacement in the publicly owned sectors (USEPA, 2000). Dignam et al. (2019) stated that the partial replacement of the lead pipes is now recognized as a contributing source for elevated lead concentrations in water. The contribution happens during the repair work to replace the lead pipe with copper; the deposits from lead used for coating the pipes can cause the buildup of lead on the pipe materials, hence releasing lead-containing materials into the water (Brown et al., 2011).

Furthermore, elevated soil lead concentration is harmful to children because kids have higher chances of ingesting soil when playing outdoors (Lanphear, 1998). In addition, the exposure becomes more harmful because their bodies absorb lead at about a 50% rate compared to 10% in adults (Alexander et al., 1974; Heard and Chamberlain, 1982; James et al., 1985; Maddaloni et al., 1998; Rabinowitz et al., 1980; Watson et al., 1986; Ziegler et al., 1978) and cause nervous system development and cognitive issues in children. Soil lead can be a legacy pollutant (e.g., on-road gasoline emissions from when leaded gasoline was still permitted) or a contemporary pollutant (e.g., secondary metal processing facilities, abraded paint) (Datko-Williams et al., 2014). In addition, lead can remain in the soil for years in the absence of remediation and other interventions (LaBelle et al., 1987). Historical air Pb emissions may still be present in the soil today despite the sharp decline in air Pb emissions in the past forty years.

2.10. Environmental injustice associated with lead exposure

The research community focusing on the environmental injustice associated with childhood lead poisoning reported the extent to which racial and ethnic minorities and lower socioeconomic class are disproportionately exposed to lead. Furthermore, most of the studies examining environmental injustice associated with childhood lead poisoning in the United States used characteristics such as socioeconomic measures of deprivation (e.g., Gini coefficient (Gini, 1997), population below the federal poverty level (U.S. Census Bureau, 2017), or socioeconomically disadvantaged (Sampson et al., 1997) to estimate the risks of eBLLs for different geographic scales (e.g., census block groups, census tracts, and zip codes) (Boutwell et al., 2016; Hanna-Attisha et al., 2003; Krieger et al., 2003; Aelion et al., 2013; Carrel et al., 2017). Thus, these variables continue to be used as critical characteristics while examining the environmental injustice associated with lead exposure.

The literature has shown that a significantly nationwide racial disparity in BLLs exists, predominantly among minority communities and communities with low socioeconomic status (SES), primarily American black children (Mahaffey et al., 1982; Pirkle et al., 1994; Meyer et al., 2003; Jones et al., 2009; Kaplowitz et al., 2010; Morrison et al., 2013; Brink et al., 2013; Whitehead and Buchanan, 2019). In addition, specific studies have associated that these population groups mentioned above tend to reside in older and substandard housing with higher lead exposure potentials (Jacobs et al., 2002; Raymond et al., 2014; Campanella and Mielke, 2008; Leech et al., 2016).

2.11. Current challenges in assessing lead exposure sources and determinants.

It is believed that many children with eBLLs are never identified and possibly do not receive interventions, thereby increasing their risk for the myriad health, educational, and social problems associated with prolonged lead exposure (Christensen et al., 2019; Bruce et al., 2019). Therefore, to reduce the effects of lead poisoning, we must quickly and proactively identify the children with the highest risk and begin environmental intervention and, if required, chelation therapy (Kaplowitz et al., 2010). Chelation is a procedure in which lead ions in the bloodstream are bonded to an organic molecule, thereby preventing the lead from entering into unwanted chemical reactions in the body of an affected individual (Kaplowitz et al., 2010). Apart from screening through blood level, which is the only feasible detection method, the CDC, in 1997, recommended an additional primary intervention to prevent exposure before it happens. The CDC developed guidelines to target BLL testing toward children at the highest risk. It was determined that the most significant risk factor for eBLL is old, poorly maintained housing. The guideline resulted in several home evaluation approaches.

The home evaluation aims to achieve better coverage in terms of estimating and assessing lead exposure risk, especially among children, with the intent being to accurately identify the highest risk groups and then connect them with interventions. Therefore, research in this area has investigated a range of physical home evaluation techniques and statistical approaches to predict the presence of children with possible lead poisoning in homes. These studies have been successful in identifying housing characteristics (e.g., floor lead loading greater than 15 $\mu g/ft^2$, rental housing, poor housing condition, paint chip in dust) (Lanphear et al., 2005) associated with children having eBLLs and also explaining the association of eBLL risk with socioeconomic status index (Boutwell et al., 2016; Hanna-Attisha et al., 2003; Krieger et al., 2003) and neighborhood deprivation index (Frostenson and Kliff, 2016; Aelion et al., 2013; Carrel et al., 2017; Wheeler et al., 2019). Further, these studies confirmed relationships between mean childhood lead levels $\geq$ 5ug/dL and low homeownership, high poverty, and race.

However, studies aimed at improving child lead exposure identification have also highlighted the challenges associated with capturing the range and combination of all possible sources of lead and their patterning by neighborhood and sociodemographic characteristics. For example, physical home evaluations are time-, resource-, and expertise-intensive and, therefore, frequently limited to small sample sizes (e.g., 351 homes) (Cluett et al., 2019). Home evaluations may also be prone to a significant degree of measurement error and are rarely paired with blood lead test data (Frostenson and

Kliff, 2016). Finally, at least historically, home evaluations have been conducted without commensurate individual-level covariate data that would be needed for incorporation into models to predict eBLLs (Wheeler et al., 2019). Therefore, for Pb prediction, the integration of blood lead test data, with the significant sources of lead exposure at the individual level, could reveal specific patterns that would provide a more accurate prediction of the possibility of childhood lead exposure in residential homes

In addition, identifying and separating the effects of multiple potential exposure factors and sources of lead affecting childhood blood lead level (BLL) is challenging. One reason is that there are many potential, highly correlated influential factors. Recently, machine learning models/techniques have been developed in many areas of health care and epidemiology research, specifically to detect patterns in data and then use the uncovered patterns to predict future data or to perform decision-making under uncertainty (Oskar and Stingone, 2020). For example, supervised machine learning models such as decision tree models (e.g., random forest) have been used for predicting childhood eBLLs (Wheeler et al., 2021; Potash et al., 2020). A decision tree-based machine learning model was compared with the traditional regressions in these studies. The result showed that machine decision tree-based models outperformed other parsimonious regressions in predicting eBLLs. Nevertheless, even in these machine learning efforts and general lead exposure studies, the integration of major multiple exposure pathways is lacking or overlooked.

Older metropolitan areas, especially in the Midwest and Northeast part of the United States, share a disproportionate burden of lead (Pb) exposure due to housing stock age and the use of lead water service lines made several decades ago (Lynch and Meier, 2020). Milwaukee County, Wisconsin, is one such example (Christensen et al., 2019), with 84% of occupied housing in Milwaukee County built before 1979 and 40% built before 1950 (U.S. Census Bureau, 2016) and more than 75,000 homes (70% of total housing stock) serviced by lead water service lines. These lead exposure pathways originate from the physical built environment; yet, they are also influenced by neighborhood social context-driven by power differentials and institutional racism. As a result, lead exposures disproportionately impact neighborhoods with low socioeconomic characteristics, older housing stock, neighborhoods of color, and neighborhoods in geographic proximity to industrial lead emissions (Mahaffey et al., 1982; Pirkle et al., 1994; Meyer et al., 2003; Jones et al., 2009; Haley and Talbot 2004; Kaplowitz et al., 2010; Morrison et al., 2013; Brink et al., 2013; CDC, 2013).

2.12. Lead Problem in Milwaukee, Wisconsin

Table 2.1 shows the demographic composition in Milwaukee County. According to the US Department of Housing and Urban Development Survey on the prevalence of lead hazards in US housing, about one-third of housing units in the Midwest have Pb hazards (compared to 25% for the overall United States). Also, older housing was more likely to be occupied by families with children (Jacobs et al., 2002). In Wisconsin, it is impossible to estimate the exact number of children at risk for eBLLs who should receive testing (Christensen et al., 2019). However, some indicators of the extent of the problem exist. For example, among the 203,068 children under six years enrolled in Medicaid in 2015, above one-third (n = 71,565; 35.2%) had never been tested for lead. In 2016 alone, 87,443 children under age 6 received a blood lead test, and 5% (n = 4,353) were

Table 2.1: Demographic composition of Milwaukee County as of 2019[a]

Variables	Percentage
Total population	945,726
Race Composition (Percentage)	
White	64.2%
Black or African American	27.2%
Asian	4.7%
Two or More Races	2.8%
America Indian and Native Americans	1.0%
Median Household income ($)	$50,606
Owner-occupied household**	49.5%
Renter-occupied household**	51.5%
Poverty Rate	19.0%
Per capital income in the past 12 months**	$29,270

[a](Source: US Census 2018 ACS 5-Year)
**Aggregate over 2015-2019

reported with elevated blood lead levels (Christensen et al., 2019). Nevertheless, the number of children tested has decreased over the past six years, with 18,000 fewer children tested in 2016 compared with 2010.

Further, the number of children tested in 2016 represents only about 22% of Wisconsin children under age six years. Therefore, it is likely that some of the children not tested was also at risk for lead exposure and elevated blood lead levels because the number indicates that not all physicians are appropriately testing children who are at risk for lead exposure (Christensen et al., 2019). Christensen et al. (2019) reported that the data presented underestimated the number of children with elevated blood lead. Furthermore, of the ten major cities in Wisconsin with at least 100 children tested in 2015, Milwaukee has had the highest prevalence of elevated blood lead levels at 9.3%.

2.13. Contribution of this study to the literature

The socioeconomic and racial inequities in childhood lead exposure in Milwaukee, Wisconsin, have been well documented. However, the relative contributions of multiple possible exposure pathways for lead are understudied. Milwaukee, Wisconsin, provides a distinctive setting to simultaneously evaluate the contributions of multiple sources of lead exposure to elevated blood lead levels (eBLLs) among children. Chapter four of this dissertation models pediatric lead poisoning and improves the interpretability of the contribution of multiple exposure sources and determinants using state-of-the-art machine learning approaches known as extreme gradient boosting (XGBoost) with Gradient boosted decision tree and SHapley Additive exPlanation (SHAP) values. In addition, this study investigates the extent to which environmental exposure profiles interact synergistically to produce comparatively higher outcomes for children with multiple exposures in Milwaukee. Finally, the study investigates to what extent the analytical approach can improve lead exposure identification and inform resource allocation to mitigate dominant routes of exposure.

2.14. References

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PROJECT C: EVALUATING BASELINE PATTERNS OF INDOOR ENVIRONMENTAL EXPOSURES AND THEIR DETERMINANTS IN PUBLIC HOUSING

2.15. Introduction

Housing is an established determinant of health. The relationships between housing and health may be driven by attributes of the social and physical environments, as well as by specific adverse environmental exposures (e.g., air pollution, lead, cold/heat) shaped by residents' behaviors, the physical structure, or products and appliances used in the home (Weich et al., 2002; Rauh et al., 2008). Poor indoor environment quality (IEQ) in homes can present significant health risks (Samet, 1993; Weisel et al., 2005; Logue et al., 2012), with some of the most vulnerable populations affected being children, seniors, and those with existing compromised health conditions (e.g., underlying respiratory diseases) (Peat et al., 1998; Emenius et al., 2004; Breysse et al., 2010).

Indoor chemical exposures are a significant public health concern because exposures are a function of both inhaled concentrations and exposure duration. The concentrations of known air pollutants are often elevated indoors, where people spend most of their time relative to time spent outdoors. Moreover, indoor concentrations of a range of air pollutants such as particulate matter (PM), nitrogen dioxide (NO_2), environmental tobacco smoke (ETS), and volatile organic compounds (VOCs) have consistently been observed at exposure levels associated with poor health outcomes, ranging from asthma exacerbation to cardiopulmonary diseases to cancer (Mendell 2007; Logue et al., 2011, 2012). Further, an average American spends 90% of their time indoors; children below three years old spend up to 100% of their time in the indoor environment, while those between 7-12 years spend 87% of their time indoors (Moya et al., 2011; Coombs et al., 2016). Moreover, with the current global pandemic, many people spend their most significant time indoors; thus, staying indoors increases exposure to indoor contaminants.

Numerous pollutant sources contribute to indoor chemical exposures. At the neighborhood level, outdoor pollutants, including gases and aerosols from point (e.g., industrial), mobile (e.g., vehicular traffic), and area (e.g., dust) sources (Abt et al., 2000; Miranda et al., 2011; Li et al., 2017; Martins and Carrilho da Graça, 2018) can enter homes and contribute to indoor air pollution. The infiltration of outdoor air pollutants into homes, especially particulate matter less than 2.5 µm ($PM_{2.5}$), is a significant contributor to IEQ (Shrestha et al., 2019). Outdoor $PM_{2.5}$ can infiltrate indoors in buildings even with closed or open windows and doors or supply air ventilation systems. Building materials and conditions such as age, volume, insulation, the airtightness of the building, vents, internal and external geometry might impact the amount of pollution that passively enters or infiltrates into the indoor air space (Hanninen et al., 2004; Taylor et al., 2014).

Another significant contributor to the indoor environmental quality is the occupant's activities in the house. Occupant-driven activities emitting air pollution include combustion-related pollutants such as NO_2, and $PM_{2.5}$ from cooking (Klepeis & Nazaroff, 2006; Evans et al., 2008; Militello-Hourigan and Miller, 2018; Olson and Burke, 2006; Wallace et al., 2004), $PM_{2.5}$ from solid fuel heating or smoking (Géhin et al., 2008; O'Leary et al., 2019; Fernandez et al., 2015; Ferro et al., 2004), candle burning (Long et al., 2000; Macneill et al., 2014), incense burning (Jetter et al., 2002). In addition, other non-combustion sources such as aerosols and solvents from cleaning products and air fresheners emit VOCs (Dumanoglu et al., 2014; Dimitroulopoulou et al., 2015). Moreover, the household cleaning activities such as vacuuming, sweeping, and dusting can create the resuspension of harmful particles into the breathing zone (Abt et al., 2000; Qian et al., 2014; Ferro et al., 2004; McCormack et al., 2008). Finally, these indoor-generated pollutants can undergo further transformation by chemical reactions on indoor surfaces. For example, the reaction of NO_2 with indoor surface materials can produce the formation of nitrous acid (HONO), a pollutant with known health impacts (Gligorovski, 2016; Ma et al., 2017).

Another component of IEQ is thermal comfort, which is influenced by the occupant's indoor comfort level with indoor climatic conditions. While not as critical as pollutant concentrations from a health perspective, thermal comfort is a significant, influential parameter for occupants' IEQ (Lai and Yik, 2009; Patino and Siegel, 2018). Indoor temperature and humidity are major underlying parameters of thermal comfort, and they serve as indicators of hygrothermal (the movement of heat and moisture through buildings) conditions. Poor hydrothermal conditions such as increased indoor humidity levels above 60%, whether emitted by occupants, indoor activities, and combustion, can cause condensation on surfaces and mold growth (Broderick et al., 2017). Mold growth could cause the proliferation of house dust mites, while humidity levels below 30% can cause sensory irritation (Crump, 2011).

Socioeconomic disparities in exposure to indoor pollutants exist (Adamkiewicz et al., 2011). The observed disparities are overwhelmingly associated with tenure status, and building type (Chu et al., 2021), as low-income earners, minorities, and people of color are more likely to rent and live in older multifamily apartment homes. These older homes tend to have higher leak rates, causing greater infiltrations from the outdoors and neighboring units (Fabian et al., 2016; Rosofsky et al., 2019; Russo et al., 2015). In addition, these households are often located in areas with higher outdoor $PM_{2.5}$ concentrations and other environmental justice concerns (O'Neill et al., 2003; Rauh et al., 2008; Rosofsky et al., 2018). It is worth noting that the existing interventions to improve indoor air quality, such as lead abatement, integrated pest management, healthy home education, and improved mechanical ventilation systems, have successfully reduced indoor environmental exposures in low-income housing (Julien et al., 2008; Chew et al., 2006; Peters et al., 2007). However, despite our understanding of the literature on the contributing factors to poor indoor air and environmental quality, much is still unknown about the relative contributions of the building and behavioral contributions to potential disparities in the indoor concentration of air pollutants.

In an attempt to identify the effectiveness and where best to direct resources and efforts to intervene on exposures, there has been a decent, albeit limited, number of studies that characterize indoor air in various settings and conditions. As a result, many different pollutants have been measured in indoor air in homes. Some of the most commonly measured pollutants include $PM_{2.5}$, NO_2, CO, VOCs (e.g., formaldehyde, benzene, acetaldehyde, naphthalene) (Logue et al., 2011; Coombs et al., 2016; Fabian et al., 2016; Mahdavi et al., 2016; Broderick et al., 2017; Chan et al., 2017; Chu et al., 2021).

A few consistent themes among field-based studies of indoor air quality, including those conducted with an express focus on low-income housing, have been that indoor concentrations have wide variations in homes. For example, indoor $PM_{2.5}$ concentrations were reported to have wide variations in homes, with evidence for exposure disparities between renters in multifamily housing experiencing a higher proportion of concentrations from non-ambient sources than homeowners in single- and multi-family housing (Chu et al., 2021). Furthermore, their exposures were mainly associated with a combination of behavioral and building factors. Given that the outdoor sources and occupants' behavior is challenging to alter at household levels, several authors recommended that proper maintenance and retrofits could play a role in improving and maintaining good IEQ (Adamkiewicz et al., 2011; Broderick et al., 2017; Chu et al., 2021). With regards to maintenance, increased requests for repairs and quick responses from the housing maintenance crew could reduce environmental exposures and improve positive health outcomes (Popkins et al., 2016). On the other hand, housing retrofits may also provide a potential avenue to reduce adverse health exposure of the residents and reduce their energy consumption in their units (Patino and Siegel, 2018). Taken together, these conclusions from work to date point to a road map for future work that could address these present challenges of reducing indoor air pollutants and contribute to reducing exposure disparities.

2.16. Contribution of this study to the literature

Homes can be significant sources of harmful pollutant exposures. Indoor levels of established and emerging pollutants, including carcinogens, endocrine-disrupting compounds, criteria air pollutants, and harmful microbes, are often elevated relative to levels measured outside the home. These exposures are essential determinants of ill health, including health conditions and outcomes that disproportionately impact children, the elderly, those with existing compromised health challenges, renters, and low-income earners living in public housing units. In recognition of the need for change in living conditions for improved long-term health among public housing residents, federal programming has taken varying forms over the years. Most recently, the Choice Neighborhood Initiative (CNI) approach developed by the U.S. Housing and Urban Development agency involves diverse, multi-level changes, including area/neighborhood conditions, physical housing structures, interiors, and neighborhood sociodemographic and economic makeup (Sheffield, 2014). One of the CNI approaches favors redevelopment of existing communities and diversification of neighborhoods to provide health and social benefits to residents (Darcy, 2010; Galster et al., 2010; Galster, 2013), which is currently the situation in Denver Housing Authority (DHA) public housing redevelopment project in Denver, Colorado.

Sun Valley and Quigg Newton are two residential complexes within the portfolio of Denver Housing Authority properties in Denver. Both social and environmental stressors heavily impact the health and well-being of Sun Valley and Quigg Newton residents. Eighty-three percent of Sun Valley households live below the poverty line, and the neighborhood's crime rate is 5.6 times the citywide average. The homes are old (year built: 1952) and close to high-density motor vehicle traffic and traffic-related air pollution. Upper respiratory conditions are the leading emergency room diagnosis for children in Sun Valley, while adults are the second. In addition, the residents are in the 93rd percentile for cancer-risk linked air pollution (DHA, 2019). In light of these challenges, Sun Valley is undergoing a comprehensive transformation plan that will replace 100% of current Sun Valley Homes and Annex (333 homes) and create approximately 200 moderate-income housing units and more than 200 market-rate units. Quigg Newton housing community has a similar situation to Sun Valley but not currently undergoing redevelopment.

The overall aim of this study is to investigate the physical and social exposures focusing on the indoor and outdoor air quality indicators and housing quality assessments of individual housing units/residents in DHA low-income homes. The specific objectives are as follows:

(a) To characterize indoor air quality in Colorado public housing and establish baseline indoor air quality conditions for future longitudinal studies of housing redevelopment impacts on occupant health and well-being.
(b) To evaluate the extent to which species-level monitoring of the chemical composition of indoor air can differentiate occupant-based from non-occupant-based sources of indoor air pollution in the existing public housing stock.

The demographics, population, and locations of the DHA homes examined in this study, as well as our experimental design, are uniquely positioned to extend our understanding and contributions to the existing literature gaps in understanding where best to direct resources and efforts to intervene on poor indoor environmental quality and exposures.

This study, shown in chapter 5 of this dissertation explains the research questions, study sites, data, sampling method, results, and discussion of our findings during the home investigation of the contributing sources of particle-phase and gas-phase emissions in the DHA homes.

2.17. References

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CHAPTER THREE

SPATIAL DISTRIBUTIONS OF SOCIO-DEMOGRAPHIC AND HOUSING-BASED HEALTH RISK FACTORS AND THEIR RELATIONSHIPS TO FLOODING HAZARDS IN THE U.S.

3.1. Introduction

Flooding is among the most catastrophic natural disasters, contributing to national burdens on social, economic, and health systems in the United States (Changnon, 2008; Smith and Katz, 2013). Moreover, future flood exposure (Wing et al., 2018) and disaster probability (Freeman and Ashley, 2017) are projected to increase over the contiguous United States (CONUS) due to changing climatic conditions (Kvočka et al., 2016; Schroeder et al., 2016; Prien et al., 2017), sea-level rise (IPCC, 2021), and population growth scenarios (Konrad, 2013; Visser et al., 2014; Muis et al., 2015), thus posing more significant risks and damage to economic and human systems. Therefore, assessing flood risk requires understanding the links between multiple spatially dependent variables, notably flooded areas, exposed populations within the flooded areas, and the underlying social vulnerability of the people.

A growing body of research has investigated associations between spatial distributions of social vulnerability and exposures to pre-and post-flood hazards (Chakraborty et al., 2014; Montgomery and Chakraborty et al., 2013; Grineski et al. 2013; Fielding and Burningham 2005; Chakraborty et al., 2019; Maldonado et al., 2016). Some of these studies suggest that flooding risk profiles vary with sociodemographic and economic characteristics. For example, race/ethnicity, income, age, gender, educational attainment (Cutter et al., 2003; Walker, 2012; Rufat et al., 2013), as well as housing type and tenure (Lee and Van Zandt, 2019; Mehta et al., 2020) have been strongly associated with extreme vulnerability to adverse outcomes associated with flooding. Often, people with the least capacity to prepare, respond and recover from flooding events also tend to live where their exposure to such events is greater (Wisner et al., 2004; Chakraborty et al., 2021). However, in other contexts, socioeconomically advantaged populations may experience greater exposure to coastal flooding risks (Qiang, 2018), potentially because the middle and upper classes inhabit real estate patterns along coasts exposed to coastal flooding. Moreover, other studies still have not revealed clear patterns of disproportionate exposure for socially disadvantaged populations (Masozera et al., 2007; Masozera et al., 2017). More nuanced insight on patterns of social vulnerability and flooding is needed to improve the development and implementation of context-specific guidance around harm prevention and reduction.

A better understanding of the intersection of flooding risk and housing type and tenure may be one way to address currently conflicting findings in the scientific literature. Specifically, we still do not understand the relationships between housing types and housing tenure vulnerable to different flood types, particularly across large scales.

Differentiating floods by type may be another way to address currently conflicting findings in the scientific literature. Floods can manifest as either large regional floods, local flash floods, coastal storm surges, and even urban drainage overflow (Rufat et al., 2015). The associated features of different flood types likewise vary and may influence their impact on surrounding communities. For instance, flash floods are distinctive for their rapid onset and extremely high water flow. In contrast, slow-rise floods (also called fluvial floods) occur due to slowly increasing river flows that eventually leave the channel banks. In both examples, the impact on homes in surrounding communities is significant but different, as flash floods tend not to influence settlement patterns. In contrast, slow-rise flooding tends to affect people living in coastal towns and cities (e.g., Hurricanes Sandy and Katrina). Thus, assessing the spatial patterns of impacted communities by specific flood types and how they intersect with patterns of social vulnerability within those affected communities is critical to identifying where, when, and for whom to distribute resources for protection against flooding.

3.2. Data and Methods

3.2.1. Data Sources and variables developed for statistical analysis.

Our analysis involved synthesizing several datasets, including established distributions of flood hazards and flooding characteristics, indicators of socioeconomic status, social vulnerability, and housing characteristics (e.g., housing type, occupant tenure) (Table 1). All data were publicly available at the census tract level or higher spatial resolution for a national-scale analysis across the contiguous U.S. (CONUS). We conducted a spatial analysis at the census tract level because it is conventionally understood to correspond to a neighborhood scale (Smiley, 2020) and reveals geographic patterns of potential population vulnerability to the disaster that can be used in the mitigation, preparedness, response, and recovery (Morrow, 1999).

Table 3.1: Datasets and their sources

Data classification	Data source	Year of Data
Flood hazard map	Wing et al. (2017)	
Flood type characteristics	Dougherty and Rasmussen (2019)	2002 - 2013
Housing types and tenure	American Community Survey	2009 - 2013
Socioeconomic variables	American Community Survey	2009 - 2013

3.2.2. Flood boundaries, characteristics, and classification

We use the fluvial and pluvial flooding boundaries of the 100-year recurrence interval flood (Wing et al., 2017). The area inundated by the 100-year recurrence interval flood represents an area with a 1% or greater probability of being flooded each year. The flooding boundaries were developed by Wing et al. (2017) using a two-dimensional hydrodynamic model of the CONUS and 30 m digital elevation area. The flooding data were validated against the Federal Emergency Management Agency (FEMA) Special Flood Hazard Area (SFHA) maps and included flooding in catchments larger than 50 km^2. For our analysis, we extracted the census tracts that lay partially or entirely within the flooding extents and experienced at least one flood episode between 2002-2013.

To classify floods by type, we relied on the work by Dougherty and Rasmussen (2019), who created a flood-producing storm database by merging storm reports with streamflow-indicated floods. Flash flood events were defined by the "rapid and extreme flow of high water into a normally dry area, or rapid water level rise in stream or creek above a predetermined flood level, beginning within six hours of the causative event." Slow-rise events were defined by "the inundation of a normally dry area caused by an increased water level in an established watercourse, or ponding of water, generally occurring more than six hours after the causative event and posing a threat to life or property" (National Weather Service 2007). These definitions were established by the National Weather Service and are widely used by the atmospheric and hydrologic science communities. The two separate resulting datasets included 20,833 census tracts that had experienced at least one flash flood and 20,970 census tracts that experienced at least one slow-rise flood between 2002 and 2013.

We further included the following explanatory variables to represent flooding characteristics: rainfall accumulation (i.e., the average flood-producing storm rainfall) and cumulative flood episodes (i.e., the total number of flood occurrences in each area), which together provided information on how different localities across the CONUS have experienced different flood types. The rainfall accumulation was derived from the 4 km, hourly Stage-IV precipitation dataset (Lin and Mitchell, 2005) over a +/-5 degree latitude/longitude grid box around the geographic centroid of flood reports from the National Center for Environmental Information (NCEI) database from 2002–2013 (Dougherty and Rasmussen, 2019). This database formed the basis for our estimates of the cumulative annual number of flooding events and average annual rainfall accumulation. We assigned them to their corresponding longitudes and latitudes in our database. To assign flooding characteristics at the census tract level, we intersected the spatial distribution of rainfall accumulation and flood episodes for flash and slow-rise floods (Dougherty and Rasmussen, 2019) in each census tract with the spatial distribution of the flooding extent (Wing et al., 2017).

3.2.3. Socio-demographic and housing data

Housing and socioeconomic variables were from the 2009-2013 American Community Survey (ACS) five-year estimates from the U.S. Census Bureau website (https://www.census.gov/programs-surveys/acs). Our housing variables included median housing age (in years), housing tenure (owner or renter-occupied housing units), and housing types by structure (single-family, multi-family, and mobile homes). In addition, we selected socioeconomic variables (Table 3) that indicate different domains of household deprivation, such as income, employment, housing, household characteristics, transportation, and demographics (Cutter et al., 2003). These variables are commonly used in distributive environmental justice research to evaluate socioeconomic variability in health outcomes and social vulnerability to natural hazards (Chakraborty et al., 2009; Grineski et al., 2015; Collins et al., 2015; Qiang et al., 2019; Khajehei et al. 2020; Smiley 2020). In defining social vulnerability throughout this study, we use the following, well-established definition: "the characteristics of a person or group and their situation that influence their capacity to anticipate, cope with, resist, and recover from the impact of a natural hazard" (Cutter et al., 2003; Wisner et al., 2004; Kron, 2005; Balica et al., 2009; Koks et al., 2015).

3.3. Methods

We investigated geographic and statistical relationships between social vulnerability and flood extent during flash and slow-rise floods. First, we employed generalized estimating equations (GEEs), a multivariate analysis technique appropriate for exploring geographic clustering of neighborhoods to provide statistically valid inferences about potential associations between flash and slow-rise flood extent and hypothesized explanatory variables (housing and socioeconomic). Second, we used multiple geostatistical approaches (Getis-Ord Gi analysis, two-way cross-tabulation, and

Local Indicators of Spatial Autocorrelation (LISA)) to examine the spatial patterning between the significant explanatory variables and flood extents.

3.3.1. Social vulnerability index

This study developed an index to represent social vulnerability using principal component analysis (PCA) with ten input variables describing the socioeconomic status and socioeconomic disadvantage (Table 3.2). These variables are commonly used indicators in social vulnerability studies (Cutter et al., 2003; Burton, 2010, Lam et al., 2016). The PCA was performed with variables standardized to a mean 0 and standard deviation 1 (i.e., z-scores). In addition, we used the Kaiser criterion to select the number of components, which retains the number of components with eigenvalues of at least 1.0 (Humpherys and Ilgen, 1969; Khajehei et al., 2020), and a minimum loading score of 0.30. The analysis yielded four components, which explains 60% of the total variance of the socioeconomic variables. The first component (PC1) explains 21% of the total variance. We used the first component (PC1) to represent a socioeconomic disadvantage, where the variables with the highest loadings on this component include census tracts with the proportion of populations limited education; households below the poverty level; households with elderly occupants; and households with children). The variables contributing to PC2, PC3, and PC4 were proportions of populations with zero-vehicle households, limited English, and single mothers, respectively. These three components explain an additional 15%, 13%, and 10%, respectively, of the overall variance.

3.3.2. Model estimation and statistical analysis

Our continuous dependent variable is the proportion of tract area flooded per census tract (flood extent), which we estimated using the ratio of flooded area to the census tract area. This variable has been modeled in previous studies (Chakraborty et al. 2019, 2021; Smiley, 2020; Tate et al., 2021) and is an appropriate choice for our study because we are interested in the distribution of social, housing, and economic vulnerabilities in areas that are susceptible to either flash or slow-rise floods. To derive the proportions of housing and socio-demographic variables in the flood zone per census tract, we assumed that each neighborhood's socioeconomic and demographic conditions are uniformly distributed (Crowell et al., 2013; Qiang 2019). Based on this assumption, the percentage of the independent variables in each tract was multiplied by the census tract flood area to estimate the proportions per census tract.

Before the model development and evaluation, we used descriptive statistics and Spearman’s correlation coefficient as a nonparametric measure to examine the statistical relationship between the explanatory variables and the flood extent (Table 3.3).

Table 3.2: The principal component analysis top components and loadings of the variables. Bold font indicates variables with high loading (> 0.30) in the principal component.

Variables	Flash Flood				Slow-rise flood			
	Principal Components (PC)				Principal Components (PC)			
	PC1	PC2	PC3	PC4	PC1	PC2	PC3	PC4
LIMITED_ENG[a]	0.294	0.200	**0.496**	0.320	0.292	0.212	**0.494**	0.313
LIMITED_EDU[b]	**0.393**	0.247		-0.130	**0.393**	0.245		-0.137
POVERTY[c]	**0.300**	-0.489	-0.411	-0.173	**0.301**	-0.493	-0.401	-0.175
NO VEHICLE[d]		**-0.567**	0.380	0.184		**-0.561**	0.388	0.181
UNEMPLOYED[e]	-0.245		-0.344	0.427	-0.242		-0.340	0.447
ELDERLY[f]	**-0.471**		0.323	-0.113	**-0.473**		0.324	-0.106
CHILDREN[g]	**-0.435**	0.296			**-0.436**	0.296		
SINGLE FEMALE[h]	-0.281	-0.126	-0.379	0.266	-0.279	-0.134	-0.377	0.256
SINGLE MOTHER[i]	-0.150			**-0.738**	-0.156			**-0.732**
NO INSURANCE[j]	0.298	0.477	-0.271		0.294	0.474	-0.282	
Proportion of variance explained	0.210	0.153	0.131	0.105	0.209	0.154	0.130	0.105

Proportions of the population: [a] with limited English proficiency; [b] above 25 with no high school education; [c] below the poverty level; [d] zero-vehicle household; [e]civilian unemployed; [f]above 75 years old; [g]below 5 years old; [h]female householder with no husband present; [i]female householder with no husband present with kids under 6 years old; [j]without health insurance.

Table 3.3: Descriptive statistics and Bivariate Correlations using Spearman's (nonparametric) relationships between tract flood extent and the explanatory variables

	FLASH FLOOD		SLOW RISE FLOOD	
	(Min, Max)	P (95% CI)	(Min, Max)	P (95% CI)
Proportion of tract area flooded (flood extent)	0.007, 0.982		0.005, 0.982	
Housing Characteristics				
Median age of homes	7.000, 81.00	0.013 (-0.006, 0.027)	7.000, 81.000	-0.022 (-0.036, 0.008)
Proportion of single-family homes	0.000, 1.000	-0.030 (-0.044, 0.185)	0.000, 1.000	-0.011 (-0.026, 0.002)
Proportion of multi-family homes	0.000, 1.000	0.171 (0.158, 0.185)	0.000, 1.000	-0.003 (-0.016, 0.010)
Proportion of mobile homes	0.000, 0.954	-0.198 (-0.211, -0.184)	0.000, 0.954	0.012 (-0.001, 0.025)
Median Household income ($)	8000, 250000+	0.122 (0.108, 0.134)	7545, 250000+	-0.004 (-0.019, 0.008)
Housing Tenure				
Proportion of owner-occupied homes	0.000, 1.000	-0.001 (-0.014, 0.013)	0.000, 1.000	0.002 (-0.011, 0.015)
Proportion of renter-occupied homes	0.000, 1.000	0.001 (-0.013, 0.014)	0.000, 1.000	-0.008 (-0.016, 0.012)
Flood and Precipitation data				
Amount of rainfall accumulation	1.000, 336.000	0.091 (0.077, 0.105)	2.000, 214.000	0.012 (-0.002, 0.025)
Number of flood episodes	1.000, 156.000	-0.146 (-0.159, -0.133)	1.000, 184.000	-0.031 (-0.045, -0.018)

Environmental Justice Factors				
Proportion limited English proficiency	0.000, 0.500	0.002 (-0.012, 0.015)	0.000, 0.500	-0.991 (-0.991, 0.990)
Proportion above 25 with no high school education	0.000, 1.000	0.006 (-0.007, 0.019)	0.000, 1.000	-0.126 (-0.139, -0.111)
Proportion below poverty level	0.000, 1.000	-0.012 (-0.024, 0.002)	0.000, 1.000	0.207 (0.194, 0.220)
Proportion zero-vehicle household	0.000, 1.000	-0.006 (-0.020, 0.008)	0.000, 1.000	-0.021 (-0.035, -0.008)
Proportion civilian unemployed	0.000, 1.000	-0.015 (-0.028, -0.001)	0.000, 1.000	0.191 (0.177, 0.203)
Proportion of population above 75 years old	0.000, 1.000	0.0002 (-0.013, 0.014)	0.000, 1.000	0.314 (0.302, 0.326)
Proportion of population below 5 years old	0.000, 0.849	-0.004 (-0.018, 0.009)	0.000, 0.849	0.115 (0.102, 0.127)
Proportion of female householder with no husband present (Single female)	0.000, 1.000	-0.005 (-0.019, 0.008)	0.000, 1.000	0.196 (0.183, 0.207)
Proportion of female householder with no husband present with kids under 6 (Single Mothers)	0.000, 0.515	-0.006 (-0.019, 0.008)	0.000, 0.515	0.105 (0.093, 0.119)
Proportion of without health insurance	0.000, 1.000	0.015 (0.001, 0.027)	0.000, 1.000	-0.071 (-0.084, -0.057)

In addition, GEEs are well suited for this study because the dependent variable has a non-normal distribution. We defined clusters of census tracts based on the median decade of housing age (1939 or earlier; 1940 to 1949; 1950 to 1959; 1960 to 1969; 1970 to 1979; 1980 to 1989; 1990 to 1999; 2000 or later). The use of median decade of housing to define clusters has been documented to match the developmental formation of the census tract (Grineski et al., 2017; Chakraborty et al., 2019). In addition, we used the quasi-likelihood under the independence model criterion (QIC) to evaluate model fit, where the lowest values indicate better fit (Pan 2001; Grineski et al., 2017; Chakraborty et al., 2019). Finally, we tested for multicollinearity using the variable inflation coefficients to combine standardized independent variables in each GEE model. There was no indication of multicollinearity in the models since all variable inflation coefficients were below 5.0. Further information on GEEs can be found in Collins et al. (2015).

3.3.3. Geospatial analysis of flood characteristics, housing, and socioeconomic indicators.

We employed three different geostatistical techniques to detect spatial clustering of statistically significant variables from the GEE models. First, we used the Getis-Ord GI analysis to detect significant hotspots (clusters of high values for a given variable or set of variables) and coldspots (clusters of low values for a given variable or set of variables) of flood characteristics. For a spot to be considered a hotspot (or coldspot), the location must have a high, positive Z-score surrounded by other high, positive Z-score values (or a low, negative Z-score surrounded by other low, negative Z-score values) (Qiang 2019; Sanchez- Martin et al., 2019; Khajehei et al., 2020).

A two-way cross-tabulation was used to map the coincidence of hotspots or coldspots for flood characteristics with housing and socioeconomic variables. Furthermore, we used the Local Indicators of Spatial Autocorrelation (LISA) to examine the spatial clustering of housing and socioeconomic indicators that were spatially non-random. LISA measures the degree to which values at one place are like those in surrounding areas. The analysis identifies clusters and outliers by identifying groupings and anomalous values according to proximity criteria. The analysis identifies clusters/regions with significant (p-value < 0.05) concentrations of high values in concordance with their surroundings (high-high, H.H.), concentrations of low values (low-low, L.L.), and spatial outliers (low-high, L.H., and high-low, H.L.) (Myers et al. 2008; Cutter and Finch 2008; Zhou et al., 2014; Koks et al., 2015; Sanchez- Martins et al., 2019). Although LISA cannot explain the causal mechanism behind the resulting spatial clusters, it helps understand the local patterns because different flood types' impacts vary widely in space and time in different census tracts.

3.4. Results

We used a non-parametric two-sample Mann-Whitney U test to examine the difference between the flood extent for flash and slow-rise floods. We found no statistically significant difference between flash and slow-rise flood extents ($P < 0.001$). Data for flash and slow-rise floods are analyzed separately, with results for each flood type examined comparatively to explore contextual differences and similarities.

3.4.1. Generalized Estimating Equations

3.4.1.1. Flash floods

The increased extent of flooding in census tracts prone to flash floods were associated with a higher proportion of mobile housing than single-family homes ($p<0.001$); a higher proportion of renter-occupancy than owner-occupancy ($p<0.001$), limited English proficiency ($p<0.01$), and increased rainfall accumulation ($p<0.001$) (Table 3.4). A one-unit increase in the standard deviation of each of these variables (i.e., the proportions of mobile homes, renter-occupancy, and population with limited English proficiency, and rainfall accumulation) was associated with a $56 \pm 0.09\%$, $11.5 \pm 0.06\%$, and $4.5 \pm 0.04\%$ increase in the likelihood of living in a flash flooded area, respectively. Thus, we observe a consistently positive association between indicators of socioeconomic disadvantage and residence in flash flood-prone areas. Further, a one-unit increase in the value for PC1 (a relative measure of socioeconomic disadvantage) is associated with a 7.3% increase in the likelihood of living in a flash flooded area; however, the trend was statistically non-significant. The cumulative number of flash flood episodes did not have a statistically significant association with flood extent.

3.4.1.2. Slow-rise floods.

As with flash floods, the increased extent of flooding (in this instance, in census tracts prone to slow-rise floods) was associated with a higher proportion of renter-occupancy than owner-occupancy ($p<0.001$), limited English proficiency ($p<0.01$), and increased proportion of mobile housing units than single-family homes ($p<0.001$) during slow-rise floods. Further, belonging to the socioeconomically disadvantaged group (as measured by the score of the first component of the PCA) ($p<0.05$) and having a lower household income ($p<0.001$) has a positive association with the 100-year flood extent. However, this pattern was not the same trend as with flash flood events, but only with slow-rise floods, and the trend was also statistically significant (Table 3.5).

A one-unit increase in standard deviation in the proportions of mobile homes, renter-occupancy, limited English proficiency, and households belonging to the socioeconomically disadvantaged group was associated with 36.9 $\pm$ 0.09%, 27 $\pm$ 0.08%, 4.8 $\pm$ 0.04%, and 2.2 $\pm$ 0.03% increase in the likelihood of living in a slow-rise flooded area, respectively. Also, rainfall accumulation is positively (and statistically significantly) associated with the increased extent of slow-rise flood extents, while the cumulative number of flood episodes was not.

3.4.2. Spatial distribution of flash and slow-rise floods.

Hotspots of rainfall accumulation associated with flash flooding were most prominent in the southeast region of the U.S. and within the Mississippi River corridor (Figure 3.1a). In addition, clusters of high rainfall accumulation associated with flash flooding were also located along the Pacific Northwest (border of Northern California and Oregon) and part of the Mid-Atlantic regions. In contrast, clusters of low rainfall accumulation associated with flash flooding were observed in the Midwest, Rocky Mountain, and Northeast regions (Figure 3.1a). Flash flood episodes were common in the South, Midwest, and Mid-Atlantic parts and uncommon in the Rocky Mountain, Upper Midwest, and the Pacific Northwest regions (Supplementary material Figure B1).

Table 3.4: Result of Generalized Estimating Equation for flash flood

Standardized Independent Variables	**Model 1** Bª (95% CI)	**Model 2** Bª (95% CI)	**Model 3** Bª (95% CI)	**Model 4** Bª (95% CI)
Intercept (B)	-3.294 (-4.830, 2.573)	-3.000 (-5.572, 1.873)	-3.360 (-5.022, 1.268)	-3.360 (-5.064, 1.226)
Rainfall Accumulation	-0.002 (-0.013, 0.017)	0.013 (-0.102, 0.283)	0.119 (0.109, 0.136) ***	0.008 (0.004, 0.034) ***
Flood Episodes	0.012 (0.008, 0.076) **	0.043 (0.012, 0.069) *	-0.004 (-0.281, 0.241)	-0.005 (-0.284, 0.243)
Mobile homes	0.022 (0.006, 0.024) ***		0.530 (0.431, 0.716) ***	0.560 (0.350, 0.828) ***
Median Income	0.139 (0.126, 0.248) ***		0.057 (0.026, 0.120) ***	0.063 (-0.578, 0.868)
Renter-occupancy	0.017 (0.003, 0.082) ***		0.280 (0.242, 0.341) ***	0.115 (0.076, 0.135) ***
Socioeconomically disadvantaged groups		0.109 (0.082, 0.293)	0.011 (-0.307, 0.329)	0.043 (-0.310, 0.333)
Zero-vehicle household		0.131 (0.113, 0.441) *	0.016 (-0.291, 0.324)	
Limited English proficiency		0.015 (0.008, 0.021) **	0.045 (0.039, 0.069) **	0.045 (0.027, 0.086) **
Single mothers		-0.016 (-0.738, 0.349)	0.021 (-0.349, 0.391)	
QIC	20910	20935	20881	20875

*P < 0.05; **P < 0.01; ***P < 0.001.

QIC (quasi-likelihood under the independence model criterion)

Table 3.5: Result of Generalized Estimating Equation for slow-rise floods

Standardized Independent Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
	B[a] (95% CI)	B[a] (95% CI)	B[a] (95% CI)	B[a] (95% CI)
Intercept (B)	-3.184 (-4.421, 2.338)	-3.432 (-3.948, 1.024)	-3.022 (-3.369, -2.674) ***	-3.033 (-5.663, -0.402) ***
Rainfall Accumulation	0.102 (0.038, 0.194) **	0.077 (0.069, 0.182) *	0.006 (-0.086, 0.098)	0.052 (0.014, 0.087) ***
Flood Episodes	0.086 (-0.058, 0.091) *	0.482 (-0.334, 0.762)	-0.010 (-0.114, 0.093)	-0.020 (-0.066, 0.025)
Mobile homes	-0.003 (-0.743, 0.048)		-0.069 (-0.758, 0.620) **	0.369 (0.250, 0.613) ***
Median Income	0.028 (0.007, 0.059) *		0.061 (-0.178, 0.300)	0.074 (0.015, 0.103) ***
Renter-occupancy			-0.185 (-0.557, 0.188) ***	0.270 (0.230, 0.309) ***
Socioeconomically disadvantaged groups		0.194 (0.045, 0.264) *	0.023 (-0.131, 0.176)	0.022 (0.013, 0.047) *
Zero-vehicle household		0.337 (0.023, 0.389)	0.021 (-0.147, 0.189)	
Limited English proficiency		0.182 (0.137, 0.226) **	0.060 (-0.195, 0.316)	0.048 (0.019, 0.105) **
Single Mothers		0.045 (-0.441, 0.732)	0.008 (-0.183, 0.199)	
QIC	20974	20982	20956	20949

*P < 0.05; **P < 0.01; ***P < 0.001.

QIC (quasi-likelihood under the independence model criterion)

Exp(B) can be described as the percentage change in the proportion of tract area covered by flood type for everyone standard deviation increases in each explanatory variable (after subtracting one and multiplying by 100)

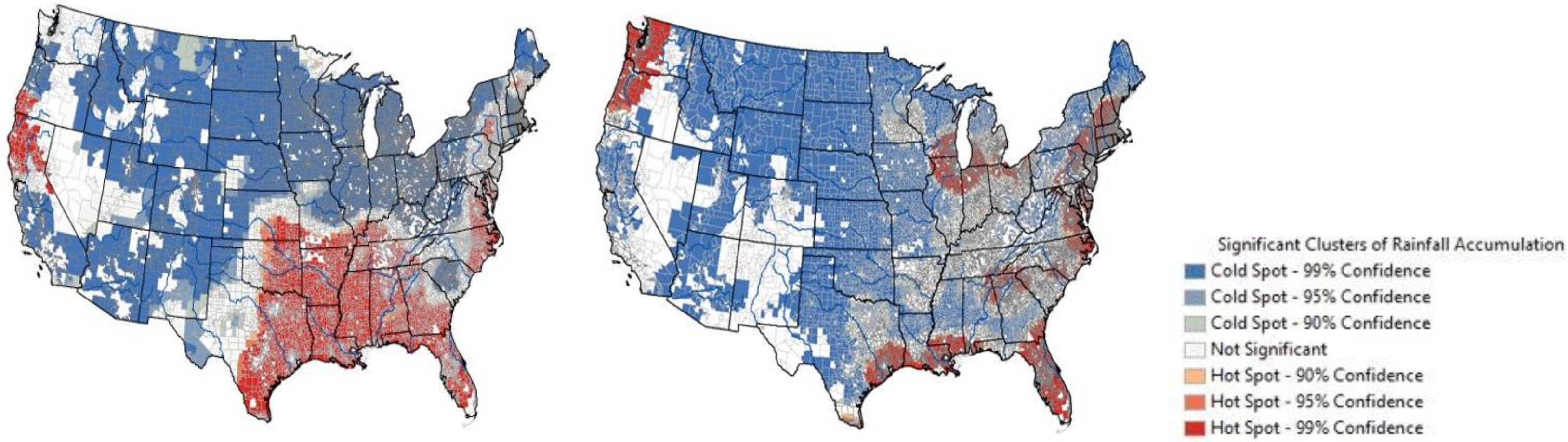
The hotspots of slow-rise flood rainfall accumulation were in the Northeast, Midwest, Pacific Northwest, and the lower Southeast along the Gulf coast (Figure 3.1a – red). Conversely, the coldspots (i.e., low rainfall accumulation causing slow-rise floods) were located throughout other regions of the CONUS (Figure 3.1b – blue). Slow-rise episodes were common in the Midwest and Northeast (Figure B2 in the supplemental material).

3.4.3. The co-occurrence of flood characteristics, housing, and socioeconomic indicators.

A two-way cross-tabulation was used to examine the intersection of hotspots or coldspots of rainfall accumulation (associated with either flash flooding or slow-rise flooding, separately) with socioeconomic and housing indicators, as described in the GEE analysis in this study. The mappings were shown at the county level because counties are well-established administrative units with similar political and governmental functions (Qiang et al., 2017). It can also be easily related to a host of social, economic, and housing data available at the census tract level.

3.4.4. Characteristics of flash floods and socioeconomic indicators.

Socioeconomically disadvantaged groups were densely clustered with flash flood rainfall accumulation (red) in the Southeast region of the United States (Figure 2a). This trend is potentially related to the lower property prices in the flood zones, which were discussed in prior studies (e.g., Speyrer and Ragas, 1991; Bin and Polasky, 2004; Bin and Landry, 2013). By contrast, socioeconomically advantaged groups were dispersed throughout the coldspots of flash flood rainfall accumulation in the Southwest and Northern plains (green), indicating that socioeconomically advantaged people were



(a) (b)

Figure 3.1: Significant clusters of rainfall accumulation associated with (a) flash floods (b) slow-rise floods. The mapping scale is at the county level.

potentially less exposed to flash flooded areas in Southwest and Northern plain regions because these regions have less rainfall accumulation causing flash floods.

Census tracts with higher proportions of renter-occupancy clustered where flash flood rainfall accumulation was high in several counties in Texas and the Southeast (Figure 2b - red), possibly because many of the characteristics associated with social vulnerability are also related to renters (Lee and Van Zandt, 2019). For example, low-income households are more associated with renting (Alexander et al., 2006; Belsky and Drew, 2007; Apgar, 2004) because they can not afford to own houses outside flood zones. In addition, census tracts with a high proportion of mobile homes were also associated with hotspots of rainfall accumulation associated with the flash flood in the Southeast region (Figure 2c - red). Prior studies have reported that mobile homes are considered more vulnerable to significant damage during floods than other housing types due to poor structural stability, solid foundation, and poverty (Shen 2005; Donner, 2007; Baker et al. 2014; Rumbach et al. 2020). In addition, mobile home residents have been associated with those characteristics of socioeconomically disadvantaged groups (i.e., living in lower house values and low incomes and overrepresented in flood hotspots compared to elsewhere (Tate et al., 2020). Furthermore, dispersed clusters of the higher population with limited English proficiency were associated with flash floods in Louisiana, Mississippi, Oregon, and New York (Figure 2d - red).

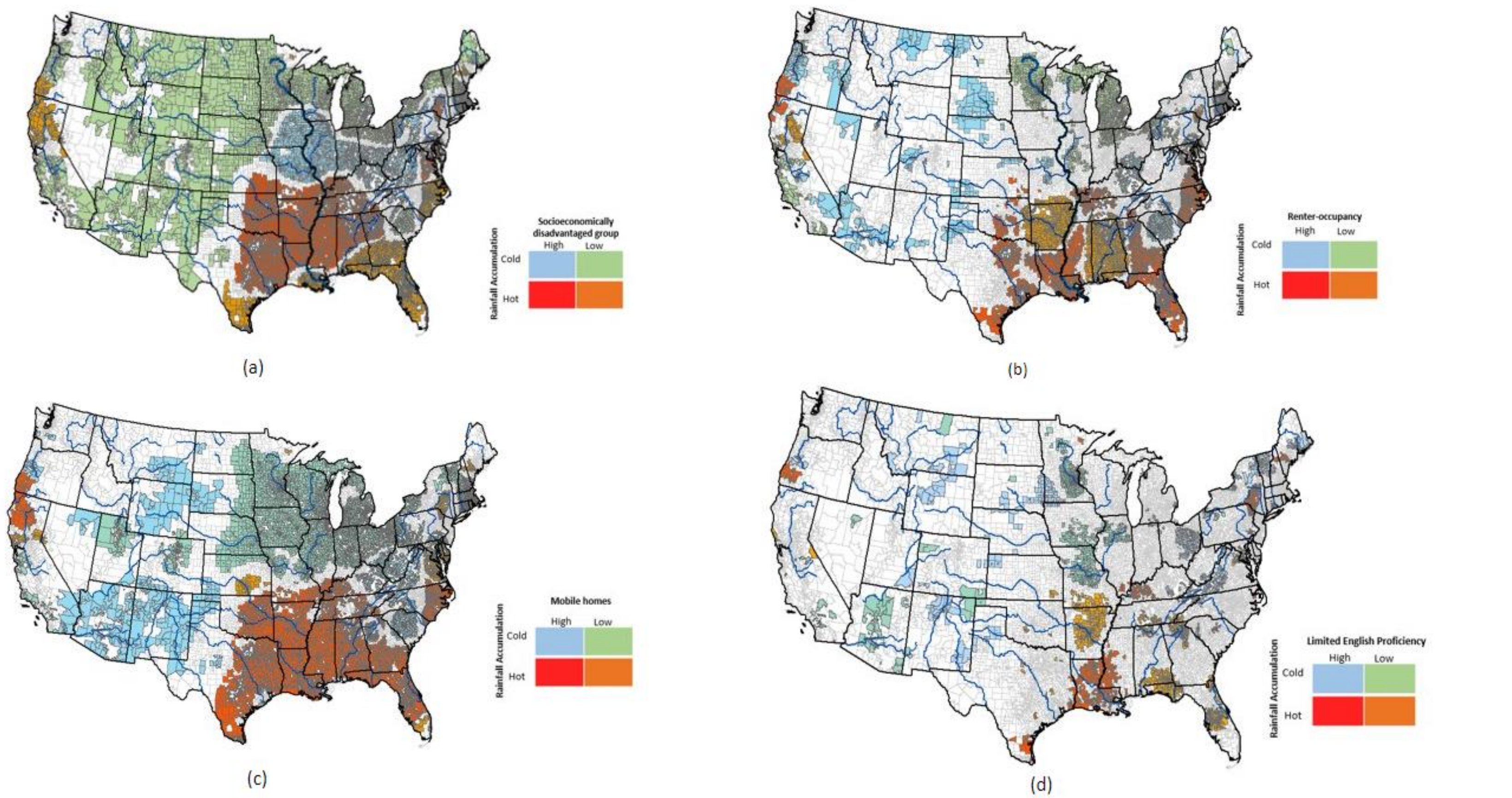


Figure 3.2: Coincidence of flash flood rainfall accumulation with (a) socioeconomically disadvantaged group (b) renter-occupancy (c) mobile homes (d) population with limited English proficiency. The mapping scale is at the county level.

3.4.5. Characteristics of slow-rise floods and socioeconomic indicators.

High socioeconomically disadvantaged groups were associated with the hotspots of slow-rise rainfall accumulation in Florida, North Georgia, and on the east coast (e.g., New York, Massachusets, Vermont, and New Hampshire) (Figure 3a – red). In contrast, socioeconomically advantaged groups associated with low slow-rise rainfall accumulation were clustered in some parts of the Southeast and Northern plains (Figure 3a – green).

Figure 3b (red) shows the Pacific Northwest and the lower Southeast region along the gulf coast have high proportions of renter-occupancies in hotspots of slow-rise floods areas. Moreover, dispersed clusters of high renter-occupancies reside in coldspots of slow-rise floods (figure 3b- blue) in other regions of the CONUS (e.g., in the Southwest and North Plains). In addition, the census tracts with a higher proportion of mobile homes associated with slow-rise flood rainfall accumulation were located in the Pacific Northwest and the Southeast along the gulf coast (e.g., Texas, Louisiana, Mississippi, North Carolina, and Florida) (Figure 3c – red). These areas along the gulf coasts were also hotspots to flash flood rainfall accumulation (Figure 2c – red), indicating that people residing in mobile homes in these locations were susceptible to flash and slow-rise flood risks. Lastly, the clusters of the higher population with limited English proficiency were associated with slow-rise flood rainfall accumulation in the south of Louisiana and Mississippi and the east coast (Figure 3d – red).

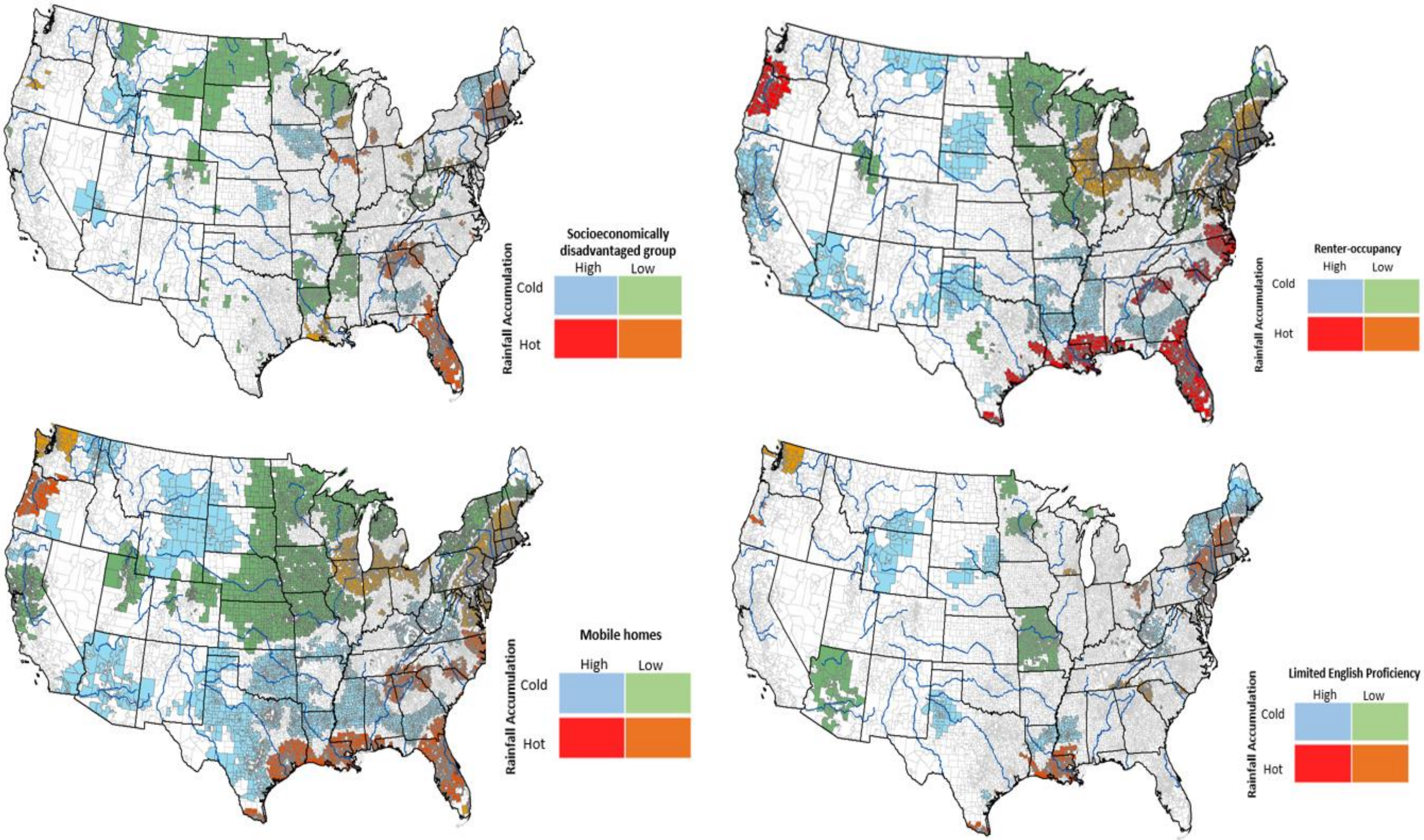


Figure 3.3: Coincidence of slow-rise flood rainfall accumulation with (a) socioeconomically disadvantaged group (b) renter-occupancy (c) mobile homes (d) population with limited English proficiency. The mapping scale is at the county level.

Cross-tabulation can reveal counties where people with certain types of vulnerabilities live in the regions impacted by specific flood types. To further examine spatial patterns of social indicators of vulnerability (e.g., renter-occupancy of homes) with flood risk at a more granular level, we used local indicators of spatial autocorrelation (LISA) (e.g., Figure 3.4). For example, high renter occupancies were more clustered in the hotspots of flash flooded areas in the Southeast (High-high) (Figure 3.4a – red). In contrast, we observed a different spatial pattern in the hotspots of slow-rise floods, where some counties have high clusters of renter occupancies (high-high) (Figure 3.4b), while some have both renters and homeowners (low-high) residing in the flood zones. Interestingly, we observed significant clusters of low renter-occupancies (low-low) (i.e., more homeowners) in the hotspots of slow-rise flooded areas on the east coast (Figure 3.4b -green), indicating more owner-occupancies have a higher likelihood of exposure to slow-rise floods in these areas.

Investigating the local spatial patterns of the socioeconomically disadvantaged groups across the CONUS, we observed a mixture of counties comprising both high and low socioeconomically disadvantaged groups neighboring areas (blue and green) in the hotspots of flash flooded areas (Figure 3.5a-inset). This pattern indicates that although the national trend shows that socioeconomically disadvantaged groups reside in the hotspots of flash floods (figure 2a). However, the local scale deviates from the general trend, reflecting that in some census tracts located in the hotspots of flash floods, both socioeconomically advantaged and disadvantaged people could be at flood risks. A similar example was observed in Florida, a hotspot for slow-rise floods (Figure 3.5b-inset). Florida has some clusters comprising both high clusters of socioeconomically disadvantaged groups surrounding each other (high-high) and areas of low and high socioeconomically disadvantaged groups neighboring each other in the slow-rise flood zones.

Household income is one of the specific indicators of socioeconomic status and vulnerability in flood-related environmental justice studies. Therefore, examining the household income of the residents in the flooded areas, a higher concentration of low-income renter-occupancy was associated with hotspots of flash flooded areas in Figure 6a- (blue) and slow-rise floods zones (Figure 6b - blue) in the Southeast. Thus, the pattern indicates that in the Southeast, low-income renters are more vulnerable to flood exposures in this region than high-income renters. In contrast, in South Florida along the coast (e.g., Broward and Palm Beach counties), high-income renters were associated with hotspots of slow-rise floods (Figure 6b - red), while low-income renters were not. Similarly, high-income homeowners reside in flooding hotspots on the East Coast, where high-income owner-occupancies were common along with coastal properties (as is also the case in many coastal regions in Florida).

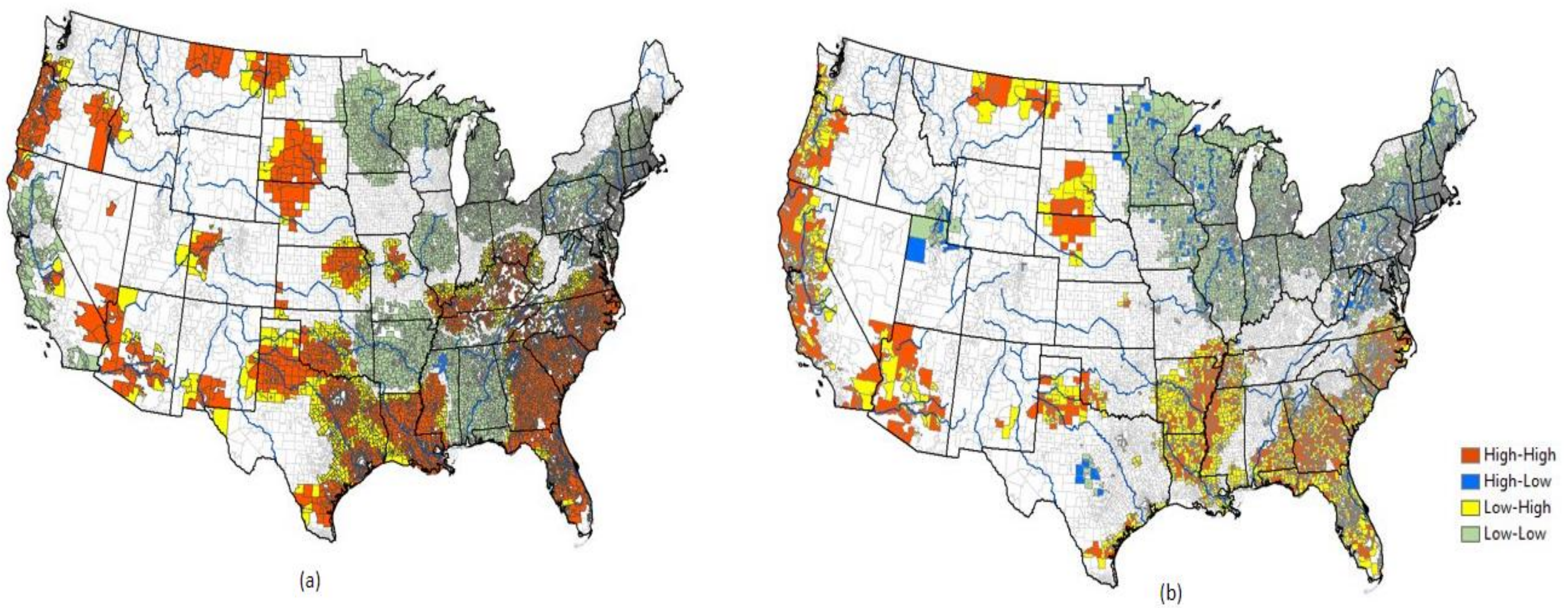


Figure 3.4: Anselin Moran's *I* cluster analysis for renter-occupancy in floodplains susceptible to (a) flash floods (b) slow-rise floods. The figure shows concentrations of high values (high–high, HH), concentrations of low values (low–low, LL), and spatial outliers (low–high, LH and high–low, HL).

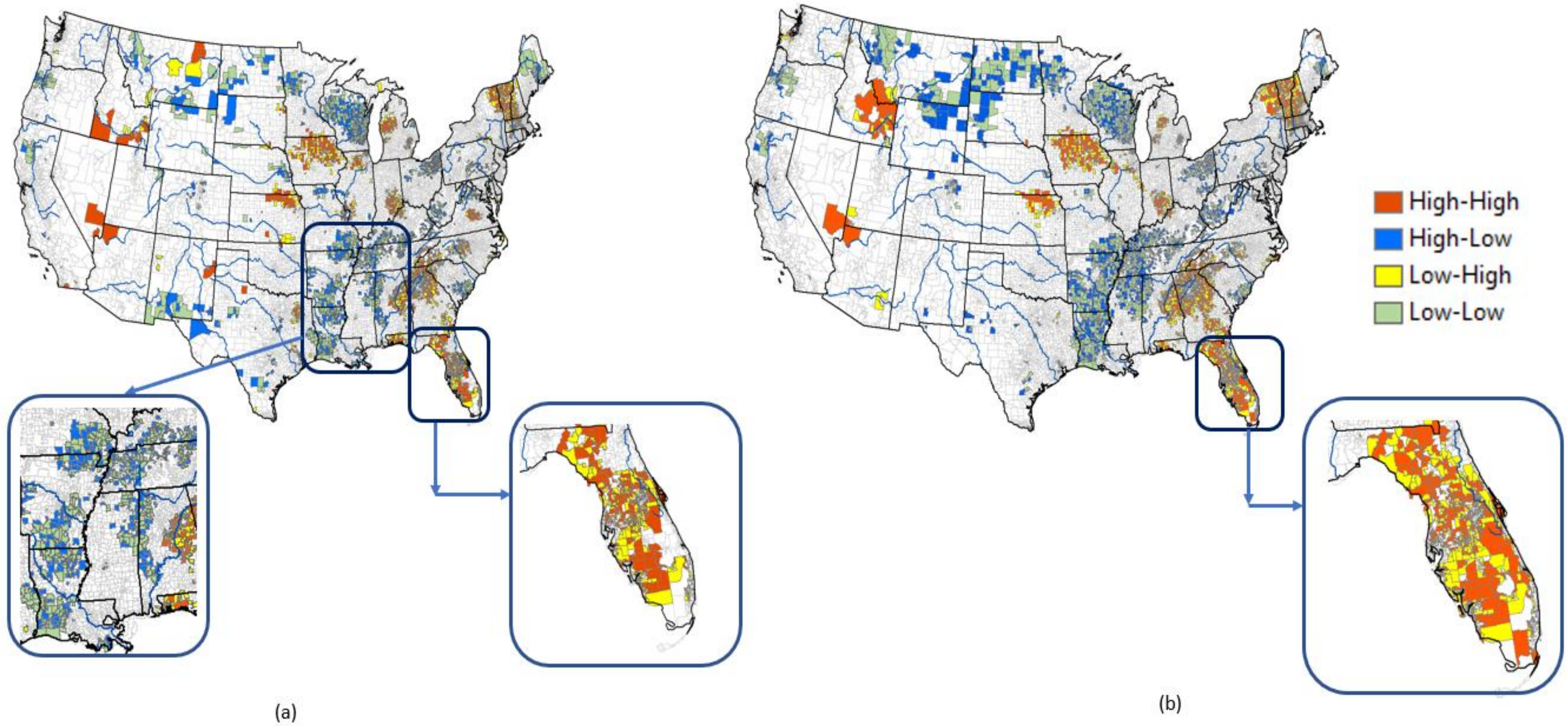


Figure 3.5: Anselin Moran's *I* cluster analysis for socioeconomically disadvantaged groups in floodplains susceptible to (a) flash floods (b) slow-rise floods. The figure shows concentrations of high values (high–high, HH), concentrations of low values (low–low, LL), and spatial outliers (low–high, LH and high–low, HL). Left Inlet (a) shows the spatial distribution inside the hotspots of flash floods in the Southeast and Florida. Right inlet (b) shows the hotspots of slow-rise floods in Florida.

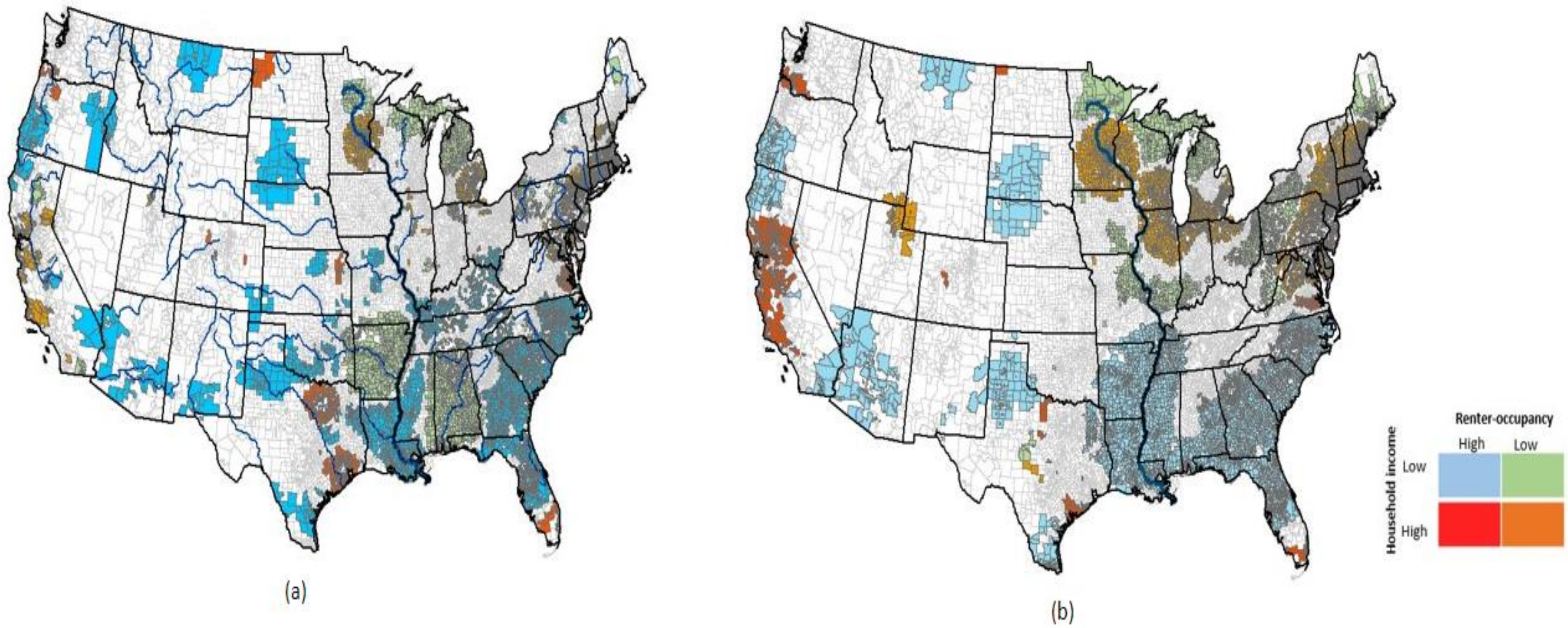


Figure 3.6: Coincidence of household income renter-occupancy in floodplains susceptible to (a) flash floods (b) slow-rise floods. The mapping scale is at the county level.

3.5. Discussion

This study sought to evaluate housing and social vulnerability indicators associated with specific flood types by using actual data on flooding characteristics (rainfall accumulation and flood episode frequency) of flash and slow-rise floods across the CONUS between 2002-2013. Thus, our first research question focuses on to what extent socioeconomically disadvantaged populations are vulnerable during flash or slow-rise floods. Our result indicates that their vulnerability varies with flood types across different regions of the CONUS. Most notably, the national trend indicates that socioeconomically disadvantaged groups were associated with slow-rise flood rainfall accumulation (e.g., in Florida and the east coast). Whereas, in the inland areas, more socioeconomically disadvantaged groups reside in the areas associated with flash flood rainfall accumulation. However, on a local scale, deviation from a national trend reflects spatial outliers where socioeconomically advantaged and disadvantaged groups neighbor one another, indicating that these two groups might be affected in certain localities.

This finding could help shape what interventions are deployed and how they are deployed. For example, we know that the duration of flood events is one of the most critical flood characteristics that affect the associated damages (Karagiorgod, Thaler, Hübl, Maris, & Fuchs, 2016; Marchi, Cavalli, Amponsah, Borga, & Crema, 2016) with slow-rise floods lasting longer than flash floods and, therefore, leading to more property damage or loss of lives. This knowledge, taken together with our analysis, could influence what regions of the U.S. have the greatest need for preventative measures against slow-rise floods and disaster relief when slow-rise floods occur.

Our second research question focused on the extent to which housing types (i.e., single-family, multi-family, and mobile housing) and tenure (i.e., renter- vs. owner-occupied housing) are associated with greater exposure to flash or slow-rise flood risks. Our analysis indicates that the exposure risks of housing types and tenure vary by flood type, whether people rent or own their homes, and according to their locations of the CONUS. However, In general, renter-occupants appear to be more likely than owner-occupants to reside where both flash and slow-rise floods occur. This result aligns with similar flood-related environmental justice studies that examined housing tenure vulnerability to flood hazards. In addition, renter-occupancies are reported to be more vulnerable than owner-occupancies and also associated with higher inundation levels (Brouwer et al. 2007), possibly leading to more adverse health impacts (Tunstall et al. 2006; Whittle et al. 2010) and higher rates of displacement and job loss (Elliot et al. 2006). However, our study shows that a higher proportion of renter-occupancies are more susceptible to flash floods than slow-rise floods in the Southeast regarding exposure to specific flood types and locations. Also, more renter-occupancies reside in slow-rise flood zones in the Pacific Northwest. In contrast, more owner-occupancies reside in slow-rise flood zones on the east coast.

The use of renter-occupancies has been reported as a salient indicator that is more influential for identifying disproportionality in disaster impacts and recovery outcomes (Jonkman et al., 2009; NASEM, 2019). For instance, it will be more informative when used more intersectional than primary indicators (Rufat et al. 2015; Rumbach et al. 2020), such as low-income renters or renter-single family or renter-multi-family. Our study observed that more low-income renter-occupancy was associated with hotspots of flash flooded areas and slow-rise floods zones in the Southeast except along specific coastal counties in Florida (e.g., Broward County). In addition, high-income homeowners reside in hotspots of slow-rise floods on the East Coast.

Prior studies such as Peacock and colleagues also investigated and found that renter-occupied single-family housing and other housing types more common to renters (e.g., duplexes and multifamily housing) were more likely to experience greater levels of damage (Peacock et al. 2014; Zhang and Peacock 2010). Although our analysis revealed that renter-occupancies are more vulnerable than owner-occupancies, but we cannot distinguish whether the most susceptible renter-occupancy are renter-single family or renter-mixed family homes (e.g., high-rises, townhomes) due to the lack of distinct datasets to investigate the tenure-structure residents that are most vulnerable and at greater levels of property damage.

Furthermore, we hypothesize that patterns of exposure to flood hazards in flash and slow-rise flood zones are correlated with patterns in housing type and housing tenure (observed at the census tract level) while adjusting for established measures of socioeconomic vulnerability remains valid. Moreover, the results presented here tend to be consistent because socioeconomically disadvantaged groups, renters-occupied homes, and mobile homes tend to be associated with hotspots of flash and slow-rise flood types. However, the spatial vulnerability differs across the CONUS.

This study focuses on patterns of social vulnerability, housing types and tenure and their relationship with flooding patterns by two different types of floods. The social vulnerability indicators examined neither include the consequences of these unequal exposures nor the indicators of resilience, risk perception, and coping capacity in the analysis. The value of our findings is enhanced when considered alongside recent insight on the temporal patterning of floods. For example, Dougherty and Rasmussen et al. (2019) investigated the seasonality that different regions of the CONUS experienced different flood types, which could inform adaptation planning, especially on local and state levels. In addition, Dougherty and Rasmussen (2020) examined how storms producing floods of different types may change in the future climate. Our study outcome could improve the allocation of actions and resources (e.g., location of an appropriate level of stormwater infrastructure) to mitigate flood risks associated with specific flood types and how they may change in a future climate.

The analyses of this study are limited in several ways, which is needed to be addressed in future research. First, socioeconomic and demographic conditions are assumed to be uniformly distributed in each census tract. This approach is common but imperfect because such conditions are often unevenly distributed throughout census tracts (e.g., urban vs. suburban vs. rural areas in the same census tract). Second, the spatial patterns of socioeconomic vulnerability that are identified represent (2009-2013) 5-year A.C.S., while the flood datasets represent an aggregate of 2002-2013. We use the estimate (2009-2013) 5-year A.C.S. as it is the most recent representation of different population subgroups closest to the last year of the flood datasets. Third, our study could not investigate the housing type-tenure-structure residents that are most vulnerable due to the lack of distinct datasets. Future studies should consider including housing type-tenure-structure datasets (e.g., renter-single family or renter-mixed family homes) as they might provide more valuable insights into the vulnerabilities associated with housing types and tenure.

The significant contributions of this study can be summarized as follows. First, this study uses the actual flooding characteristics (rainfall accumulation and flood episodes) to provide a census-tract level assessment of social vulnerability, housing types, and tenure exposure to two major flood types for the CONUS. The assessment provides empirical evidence of socioeconomic and housing tenure disparities and environmental injustice associated with different flood types in the CONUS. Second, the spatial analyses reveal local deviations from the general trends indicating how socioeconomically disadvantaged and advantaged populations are affected differently during different flood types, depending on the region in the U.S. is considered. The result offers valuable insights into how specific flood types could impact different populations and housing tenure across the CONUS.

3.6. Conclusion

This study adds to our rapidly evolving understanding of how impacts of flooding are distributed among the U.S. population. In addition, specifically, our work contributes two essential findings. First, we found that the vulnerability of socioeconomically advantaged populations is more strongly associated with exposure to floods arising from slow-rise conditions than flash flood conditions in locations like Florida. Meanwhile, this finding enlightens how different places and people are locally and nationally affected by different flood types across the CONUS. Our findings further inform strategies to support urban and rural community resilience and planning on local and state levels.

3.8. References

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CHAPTER FOUR

INVESTIGATING PATTERNS AND SOURCES OF VARIABILITY IN CHILDREN'S BLOOD LEAD LEVELS IN MILWAUKEE COUNTY USING MACHINE LEARNING MODELS

4.1. Introduction

Childhood lead poisoning remains a persistent environmental public health concern in the United States. Blood lead levels exceeding 5 µg/dL indicate lead poisoning, as defined by the Centers for Disease Control and Prevention (CDC). Nonetheless, no safe blood lead level in children has been identified. Low blood lead levels (i.e., < 5 µg/dL) in children are also associated with neurodevelopmental and cognitive issues, low intelligent quotient (IQ), learning disabilities, and hearing problems. (Canfield et al. 2003; Chiodo et al. 2004; Zhen et al. 2018; Lanphear et al., 2000; Sanders et al., 2009; Grandjean and Landrigan 2014; Yeter et al., 2020). Sources of early childhood lead exposure in the United States include lead paint in housing built before 1978 (Jacobs et al., 2002; Cantor et al., 2019); contaminated drinking water from the deterioration of leaded household service lines (Hanna-Attisha et al., 2016); house dust and contaminated soil (Mielke et al., 2016; Laidlaw et al., 2016; Ceballos et al., 2016; Entwistle et al., 2019); some consumer products (e.g., toys); and lead-emitting industrial emissions (Gallons et al., 2006).

Older metropolitan areas, especially in the Midwest and Northeast part of the United States, share a disproportionate burden of lead (Pb) exposure due to old housing stock age and the use of lead-pipe water service lines made several decades ago (Lynch and Meier, 2020). Milwaukee County, Wisconsin, is one such example (Christensen et al., 2019), with 84% of occupied housing in Milwaukee County built before 1979 and 40% built before 1950 (U.S. Census Bureau, 2016). In addition, about 164,000 water service lines are in Milwaukee, and approximately more than 75,000 (~46%) are lead water service lines (the City of Milwaukee, Lead Service Line Program Semi-Annual Updates, 2019). Previous studies have reported that elevated blood lead levels (eBLL) (i.e., BLL > 5 µg/dL) were predominantly in low homeownership, higher poverty, and majorly non-white census tracts in Milwaukee county neighborhoods (Lynch and Meier, 2020). In addition, the synergistic effect of the low homeownership, higher poverty, and majorly non-white census tracts was associated with higher blood lead levels than high homeownership, low poverty, and majorly white-dominated census tracts. In 2015, of all the Wisconsin cities with at least 100 children tested for lead, the city of Milwaukee, which is the largest city in Milwaukee County, had the highest proportion of elevated blood lead levels (eBLL) (i.e., BLL $\geq$ 5 µg/dL) of 9.3%, higher than the 2015 statewide rate of 4.6% (Christensen et al. 2019).

As a form of intervention, different government agencies (U.S. Housing and Urban Development's Office of Lead Hazard Control and Healthy Homes, the Wisconsin Department of Health Services Childhood Lead Poisoning Program (WCLPP), and other local government agencies (e.g., City of Milwaukee)) are making significant progress in protecting children from harmful lasting effects of elevated blood lead levels. Efforts include federal funds to help eliminate dangerous lead-based paint from lower-income homes and support cutting-edge research on methods for assessing and controlling housing-related health and safety hazards. At the state and local level, efforts include universal testing all the children in Milwaukee (Christensen et al. 2019) and replacing lead service lines.

Of 76,298 lead service lines in Milwaukee County, 2462 (~3.2%) have been replaced between 2016 and 2019. While these efforts are commendable, the cost of lead-pipe water service line replacement remains a challenge. The average total replacement cost per private and public residential property is \$5,587 and \$5,096, respectively (the City of Milwaukee, Lead Service Line Program Semi-Annual Updates, 2019). However, to create practical mitigation efforts and strategies, there is a need to investigate the primary contributing sources of lead in residential homes across Milwaukee County.

One significant barrier to addressing adverse lead exposures is that many children with elevated blood lead levels (eBLLs) are never identified and receive interventions. (Bruce et al., 2019). In addition, the sooner interventions and treatments (e.g., chelation therapy) can begin, the more effective they have proven to be (Kaplowitz et al., 2010), making early identification of eBLLs a significant implementation barrier to address. To aid this effort, research studies in this area have investigated a range of physical home evaluation techniques and statistical approaches to predict the presence of lead in homes. The motivation behind the approach is to identify and eliminate lead sources in homes and prevent future exposures to people living in the same residence. Interestingly, these studies have been successful in a few ways, such as identifying housing characteristics associated with children having eBLLs (e.g., Lanphear et al., 2005);

explaining the association of eBLL risk with socioeconomic status index and neighborhood deprivation index (e.g., Boutwell et al., 2016; Hanna-Attisha et al., 2003; Krieger et al., 2003; Frostenson and Kliff, 2016; Aelion et al., 2013; Carrel et al., 2017; Wheeler et al., 2019; Lynch and Meier, 2020).

Furthermore, these studies have confirmed relationships between mean childhood lead levels > 5ug/dL and low homeownership, high poverty, and race. However, studies aimed at improving child lead exposure identification have also highlighted the challenges associated with capturing the range and combination of all possible sources of lead. For example, in-person physical home evaluations are time-, resource-, and expertise-intensive, resulting in a limited sample size for statistical analysis and prediction of homes with possible lead exposures (Cluett et al., 2019). Other challenges include inaccurate or lack of blood lead test data (Frostenson and Kliff, 2016); and the absence of individual-level covariate data for predicting eBLLs (Wheeler et al., 2019).

In addition, identifying and separating the effects of multiple potential exposure factors and sources of lead affecting childhood blood lead level (BLL) is challenging. One of the reasons is because there are many potential, influential factors with co-association. Research studies have tackled this challenge using different approaches and statistical methods. For example, Zhen et al. (2018) used spatial generalized linear models (including Poisson, negative binomial, Poisson Hurdle, and negative binomial Hurdle models) to predict the number of children's lead poisoning cases using the three predictor variables (i.e., building year and town taxable value of houses, and soil lead concentration) at the census block level in the inner city of Syracuse, New York. Other studies modeled elevated blood lead level risk in a zip code using Vox lead exposure risk score, weighted quantile sum(WQS) regression, and a Bayesian SES index mode (Wheeler et al., 2021).

Interestingly, these studies showed the positive associations between building year and taxable value and an elevated risk for lead poisoning (Zhen et al., 2018). In addition, Wheeler et al. (2021) showed a statistically significant association between socioeconomic index, socioeconomic status, and elevated blood lead level risks. However, the authors had challenges with the methods. For example, the Poisson model was not a good candidate model because of the overdispersion of the dataset due to the restricted assumption of equal means and variance (Zhen et al., 2021). In addition, other methods that accounted for excessive counts of zero could not account for the interaction effects and contribution of multiple lead exposures to pediatric blood lead levels.

Recently, machine learning supervised models and techniques are being used in many health data to detect patterns and then use the uncovered pattern to predict health outcomes. The shift occurs for several reasons: machine learning methods offer a powerful and flexible alternative to explore important patterns evident in large exposure data sets that help to address complex problems, often with substantially better predictive accuracy than traditional statistical approaches, such as general linear regression (Liu et al., 2021). For example, in Chicago, Wheeler et al. (2021) compared traditional statistical methods - logistic regression and supervised machine learning model -decision tree in predicting childhood lead poisoning. The models were assessed using the area under the receiver operating characteristic curve (AUC) and confusion matrix metrics (positive predictive value, sensitivity, and specificity) at various thresholds. The result showed that the decision tree outperformed the logistic regression with a higher AUC and predictive accuracy score (Wheeler et al., 2021). Nevertheless, many studies have yet to examine the cross-influence of multiple exposure sources in a residential home to elevate blood lead level risks.

Machine learning modeling has demonstrated predictive capabilities; it is considered a “black box” due to the complex inner structure of the model (Morcada Torres et al., 2021). However, recent advances in “interpretable machine learning” have helped reveal the black boxes, making the method more attractive. Furthermore, the application of interpretable machine learning could help reveal the specific patterns and cross-influence of multiple variables in a predictive model. Therefore, for Pb prediction, the integration of blood lead test data, with the significant sources of lead exposure at the individual level, could reveal specific patterns that would provide a more accurate prediction of the possibility of childhood lead exposure in residential homes.

In this study, our specific research questions are: (i) what are the relative contributions of each potential source of exposure (i.e., housing characteristics, lead pipe water service lines, and soil lead concentration) to blood lead levels among the children between the ages 1-5 living in Milwaukee County? (ii) To what extent do environmental exposure profiles interact synergistically to produce comparatively higher BLL outcomes for children in multiple exposures? Moreover, (iii) To what extent this analytical approach can improve lead exposure identification and inform resource allocation to mitigate dominant routes of exposure?

We used the XGBoost (extreme gradient boosting) and SHapley Additive exPlanation (SHAP) to answer our research question because XGBoost is considered a highly effective scalable machine learning system due to its easy parallelism and high prediction accuracy. In addition, XGBoost uses a more regularized model formalization to control over-fitting, which gives it better performance. Additional details about XGBoost are discussed in section 4.2.

4.2. Data

4.2.1. Data Source and Study Population

4.2.1.1. Blood Lead Levels

In this study, the target variable was the blood lead levels (µg/dL). The Department of Public Health under the Wisconsin Department of Health Services (DHS) provided the Healthy Homes and Lead Poisoning Surveillance system data (HHLPSS) of children's BLL who resided in Milwaukee County from 2015 to 2019. The BLL test records the child's test ID, test date, test type, child's age at the testing date, gender, race, and primary addresses. Three different sampling methods types: venous, capillary, and unknown tests, were used to measure blood lead levels. The highest BLL obtained from the venous test was retained if a child had multiple tests. If no venous test was performed, the highest BLL obtained from the capillary blood draw was retained. Finally, if the only test result provided was one for which the test type was unspecified, the test result was used in the analysis. The tests of the unknown type comprised < 2% of all available test data.

Figure 4.1 shows the flow chart used to select the number of blood lead level observations in the study. The total number of unique observations in Milwaukee county was 95659. We identified BLL $\geq$ 5 µg/dL as elevated blood lead level. The percentage range of BLL < 5 µg/dL from 2015 to 2019 ranges between 85 – 91% while BLL > 5 µg/dL ranges from 9 – 15% (Figure 4.2).

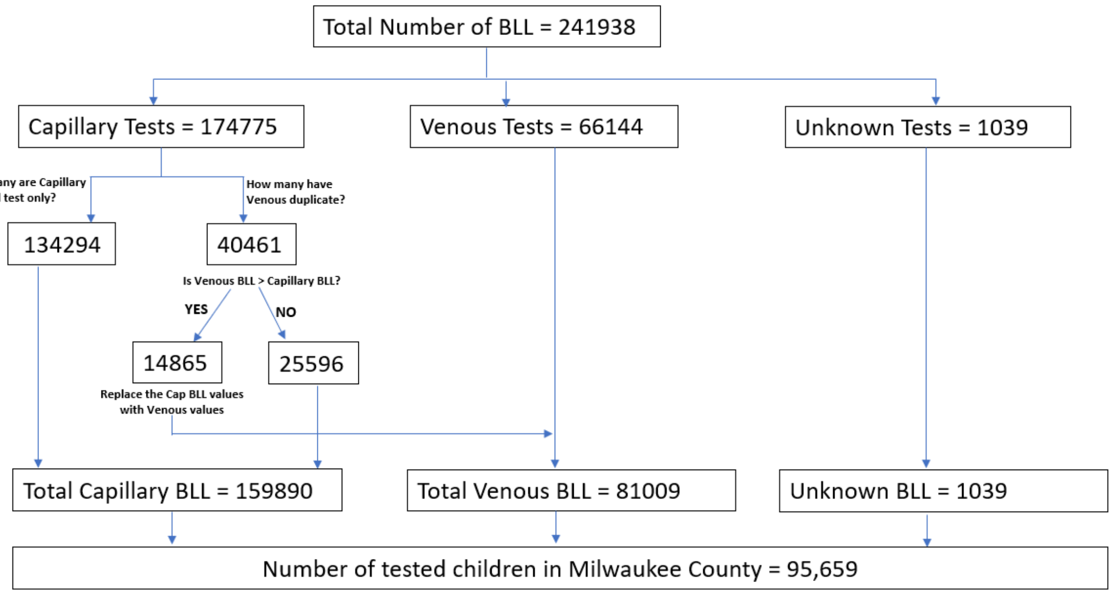

Figure 4.1: Flow chart showing the mining process of blood lead level datasets

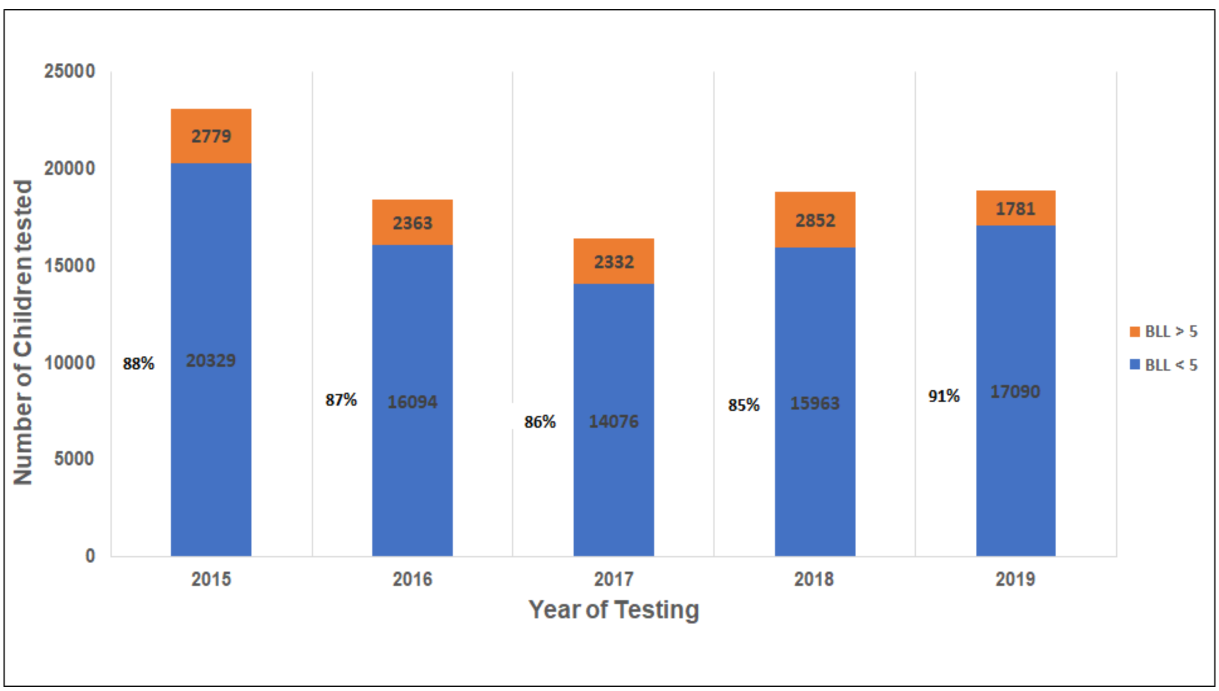

Figure 4.2: Number and percentage of children test for blood lead levels per year in Milwaukee County.

4.2.1.2. Imputation of missing BLL values

Figure 4.3 shows the frequency distribution of the children's blood lead levels in Milwaukee County. Figure 4.4 (a & b) shows the frequency distribution of the children's BLL < 5 µg/dL and ≥ 5 µg/dL. The BLL values reported as a categorical value (< 3.3 µg/dL) were imputed to continous values using the bin weight distribution of other continous BLL values. Figure 4.5 shows the frequency distribution of the BLL < 5 µg/dL after the imputation.

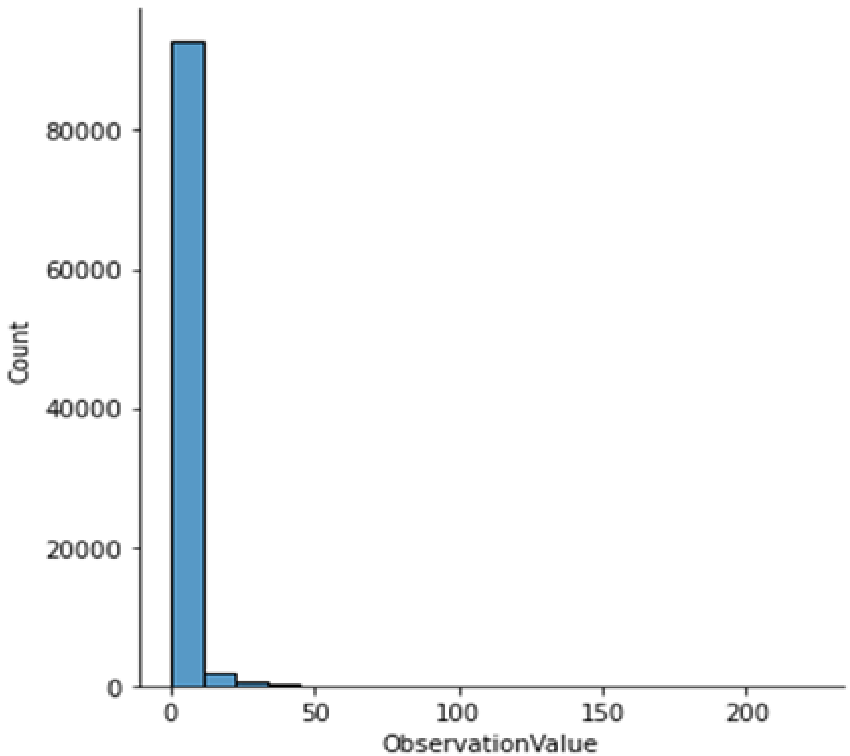

Figure 4.3: The frequency distribution of the tested blood lead levels in Milwaukee County.

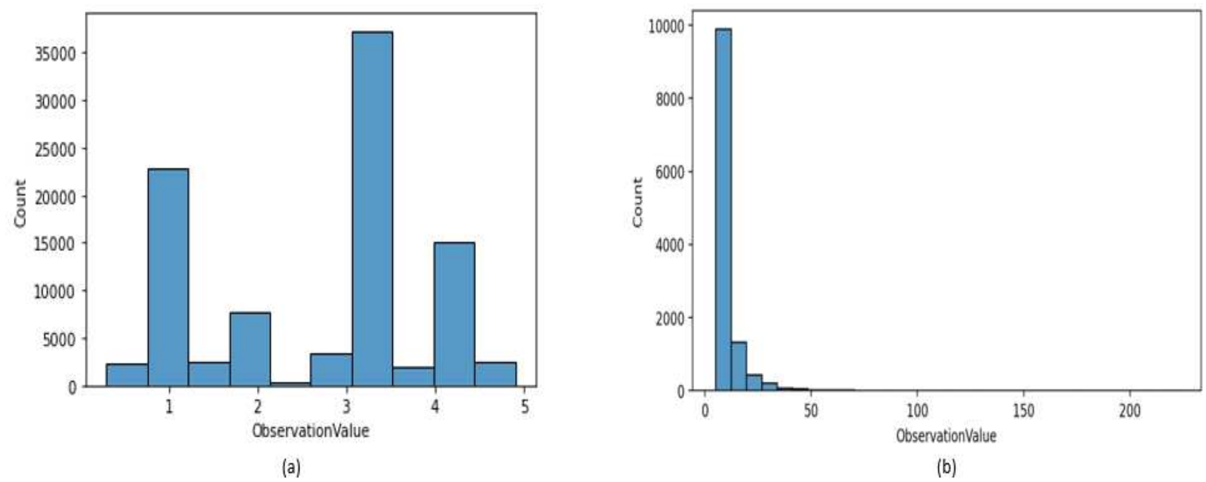

Figure 4.4: The frequency distribution of the children with (a) BLL < 5 µg/dL and (b) BLL $\geq$ 5 µg/dL

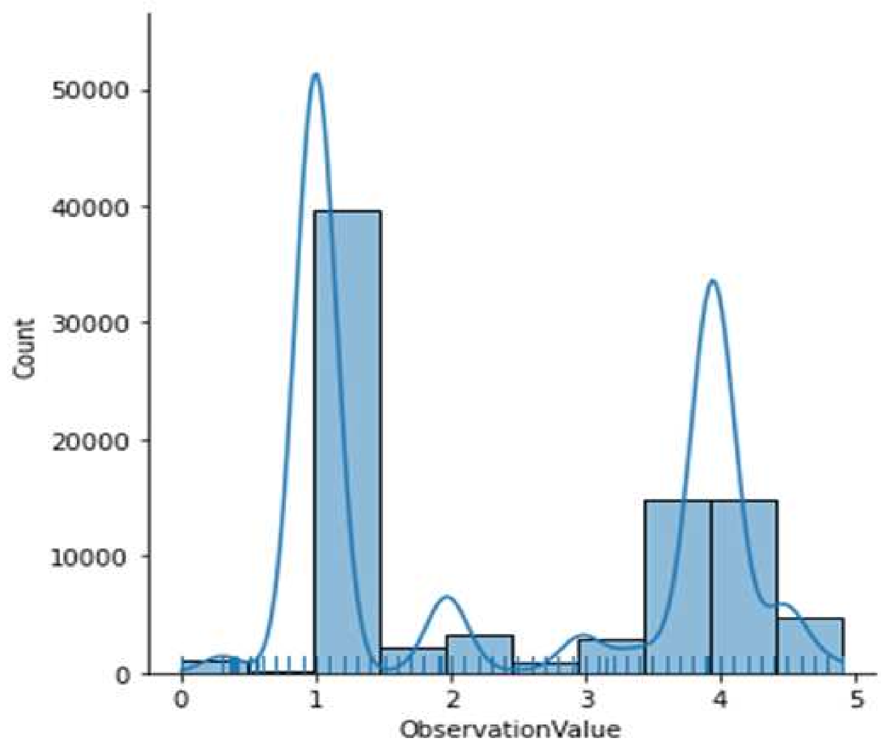

Figure 4.5: The frequency distribution of children with BLL < 5 µg/dL after imputation.

4.2.2. Major Sources of Lead

4.2.2.1. Housing Characteristics

The 2019 tax parcel data for all the residential and commercial buildings in Milwaukee County was purchased from a commercial vendor, Attom Data Solutions, Irvine, California. The data contains all the building's physical characteristics, building age, tax accessor's value, improvement values, and addresses (Table 4.1). The oldest residential building was built in 1820 (199 years), and the newest was built in 2015 (4 years). The median housing age was 1912 (98 years).

4.2.2.2. Soil Lead Concentration

The soil samples were collected and analyzed by the United States Geological Survey between October 2006 – November 2007 (Stensvold, 2011). The soil samples were sparsely and randomly taken at different locations in Milwaukee County. The soil lead concentration ranges from 23.22 - 27.75 mg/kg, while the average concentration was 25.64 mg/kg.

4.2.2.3. Lead Service Lines

In 2016, the city of Milwaukee started replacing lead service lines in Milwaukee. On January 1, 2017, the city of Milwaukee mandated that complete lead-pipe based water service lines be replaced by copper when (i) a leak or failure has been discovered on either a privately or utility-owned portion (ii) the utility-owned portion is replaced on either a planned or emergency basis (iii) the property is a child-care facility. About 76,298 lead service lines were currently made of lead pipes, and about 70,000 (91.7%) were serving residential homes (https://city.milwaukee.gov/ImageLibrary/Groups/WaterWorks/Lead-Service-Lines/2019JulySemiAnnualLSLRReportMWW_190717.pdf)

Table 4.1: Description of the features used in the machine learning model

Variables	Description	Data Type
Property Value	The tax assessor's determination of the property value	Continous
Property Area	The square footage of the building	Continous
Finished Basement Area	The square footage of the building's finished basement	Continous
Property Finished Area	The square footage of the building's finished area	Continous
Lot size	The overall square footage of the property	Continous
Bedrooms	The total number of bedrooms for all structures on the property	Continous
Rooms	The total number of rooms for all structures on the property	Continous
Stories	The total number of stories for all structures on the property	Continous
Units	The total number of housing units for all structures on the property	Continous
Building Age	The year in which the primary structure was built on the property	Continous
Soil lead Concentration	The soil lead concentration	Continous
Lead Service Lines	The presence of a lead-pipe water service line	Binary
Owner Occupancy	The homeowner presently occupies the building	Binary
Cooling Mechanism	The presence of a cooling mechanism on the property	Binary
Fireplace	The presence of a fireplace on the property	Binary
Garage	The presence of a garage on the property	Binary

Table 4.2 shows pair of variables that correlate with each other. Features with asterisks were included in the machine learning model.

4.3.3. Imputation of missing observation in the predictors

Missing data is a common problem in statistical analysis and machine learning. Accounting for missing data is necessary for evaluating data quality, knowing that the missingness can be from different sources and mechanisms. We assumed the missing observations in the housing features are missing completely at random (MCAR). It means that the nature of the missing data is not related to other missing or variables or the missingness on the variable is unsystematic. Therefore, we used the Multivariate Imputation by Chained Equations (MICE) to deal with the missing observations. The method is based on fully conditional specification, where a separate model imputes each incomplete variable. The MICE algorithm can impute mixes of continuous, binary, unordered categorical, and ordered categorical data.

Table 4.2: Pair of correlated physical housing variables

Correlated Variables	**Pearson r (%)**
Building Age** & Mechanical Ventilation	88
Finished** & Unfinished Basement Area	79
Property Area** & Living Area	100
Bathrooms & Bedrooms**	95
Property Value** & Property Improvement value	89
Property Value** & Tax Value	89

*** Features that were included in the machine learning model*

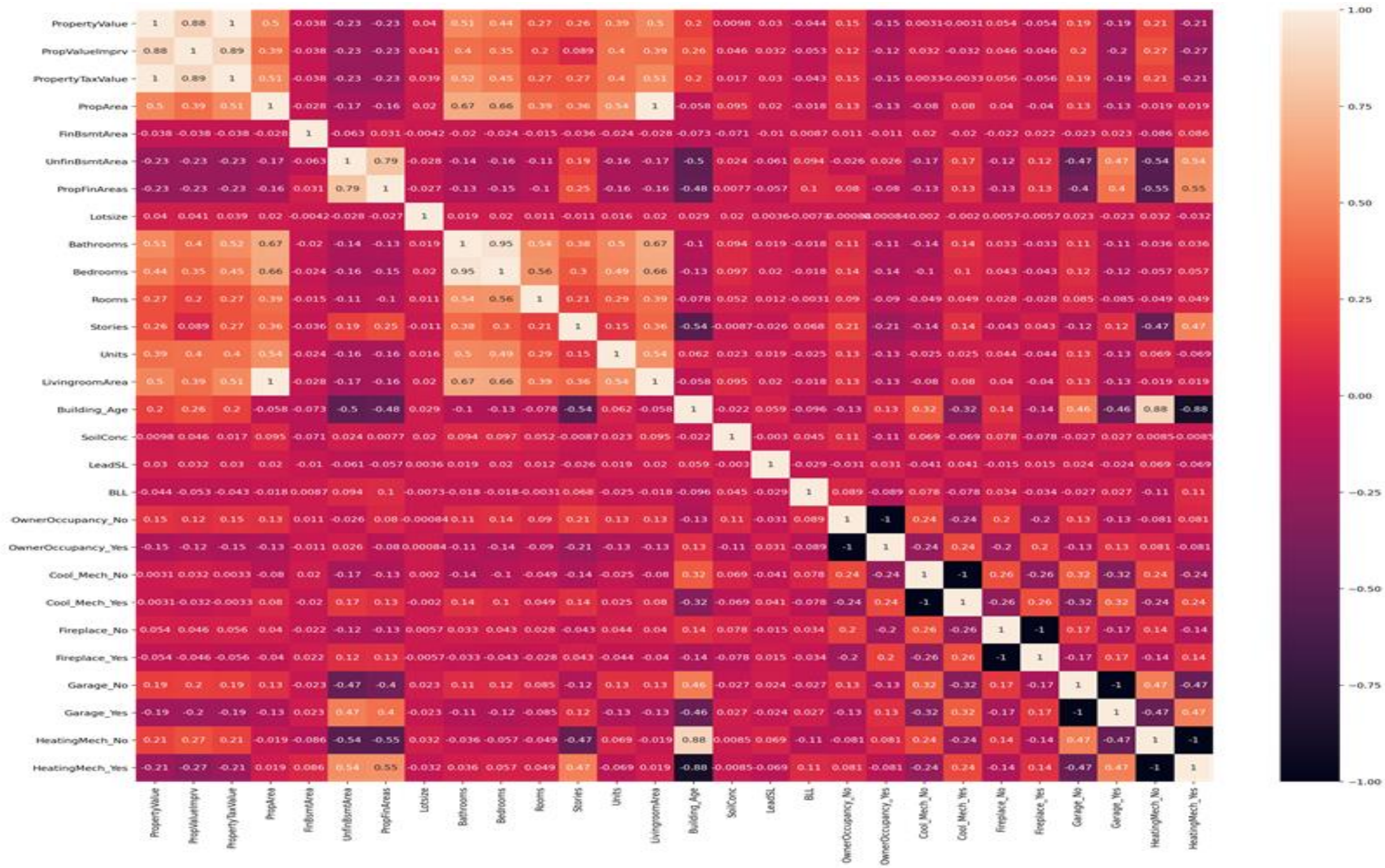

Figure 4.6: The pairwise correlation plot for 28 variables: housing characteristics, lead service lines, and soil lead concentration.

4.4. Methods

4.4.1. XGBoost (Extreme Gradient Boosting)

The term gradient boosting consists of two terms, gradient and boosting. Boosting is loosely defined as combining multiple simple models into a single composite model. With more simple models, the overall model becomes a stronger predictor. In boosting terminology, the simple models are called weak models or weak learners. Ultimately, the gradient boosting approach uses a gradient descent approach to create weak models whose collective ability to predict an outcome of interest is significantly better than any single model alone. Individual prediction models within the ensemble identified as “weak” based on their associated loss function (Loss function is the difference between the actual and the predicted value). Therefore, extreme gradient boosting improves upon the base of the gradient boosting framework to enhance execution speed and model performance.

Since the introduction of gradient boosting in 1999 by Jerome Friedman, XGBoost has been widely used in many fields to achieve state-of-the-art results on some data challenges (Zhang et al., 2019). The approach is considered a highly effective scalable machine learning system for tree boosting (e.g., gradient boosting) due to its easy parallelism and high prediction accuracy. However, this approach will provide high prediction accuracy but cannot explain the interaction effects of the variables (drivers and sources) of childhood eBLLs (Lundberg et al., 2020).

4.4.2. TreeExplainer and Shapley Addictive Model (SHAP)

Local model interaction is required to examine the interaction effect of the drivers and sources of childhood BLL. Local model interpretation is a set of techniques to help answer two fundamental questions about our model: (i) Why did the model make this specific prediction? Furthermore, (ii) What effect did individual/specific variable values have on the prediction? However, the current local explanations or interpretations for tree-based machine learning models are inconsistent. Consistency is critical for an explanation method since it makes comparisons among feature importance values more meaningful. The use of TreeExplainer provides local explanations with guaranteed consistency (Lundberg et al., 2020).

TreeExplainer is a package for explaining and interpreting predictions of tree-based machine learning models. Interpretability, in this context, means the degree of importance of a variable toward a model's final prediction or output. It also extends local explanations to measure interaction effects between predictive variables (Fujimoto et al., 2006). Traditionally, local explanations based on variable attribution assign a single number to each input feature. However, the simplicity of this natural representation comes at the cost of conflating main and interaction effects (Lundberg et al., 2020).

The use of SHAP interaction values provides a richer type of local explanation. These values use the "Shapley interaction index" from game theory to capture local interaction effects (Strumbelj and Kononenko, 2014; Lundberg and Lee, 2017; Sundararajan and Najmi, 2019). The use of Shapley values initially proposed in game theory literature provides a theoretically grounded way to measure the local interaction effects. Furthermore, the approach allocates credit not just among each variable in the model but among all pairs of individual variables. By enabling the separate consideration of interaction effects for individual model predictions, TreeExplainer can uncover significant patterns that might otherwise be missed (Shortlife and Sepúlveda, 2018; Lundberg et al., 2018).

Combining local explanations from TreeExplainer across an entire dataset enhances traditional global representations of feature importance in the prediction of BLL by (i) avoiding the inconsistency problems, (ii) increasing the power to detect true variable dependencies in a dataset, and (iii) enabling us to build SHAP summary plots, which succinctly display the magnitude, prevalence, and direction of a variable's effect (Lundberg et al. 2020). In addition, SHAP summary plots avoid conflating the magnitude and prevalence of an effect into a single number and may also reveal rare high magnitude effects.

4.5. Model description

The training cohort and test set consisted of children enrolled in State of Wisconsin's lead tracking database; Women, Infants, and Children's (WIC) enrollment data; and the Medicaid claims database tested for blood lead levels under the HHLPSS from 2015-2019. The datasets contain 93205 observations and 16 features after removing the correlated variables (Table 4.2). The datasets were split into training and test set using the blood lead testing year. The training dataset ranges from 2015 - 2017 and contains 55,497 observations. The test datasets range from 2018 - 2019 and contain 37,708 observations.

4.5.1. Model training

We trained the training set data using XGBoost using the parameters shown in table 4.3 and cross-validating the specified parameters in 5 folds and 70 interactions. In addition, Bayes optimization was used to tune the hyperparameters using eight interactions with eight steps of random exploration with an acquisition function of expected improvement. Then, we extracted the best sets of parameters for predicting the BLL values. Statistical package Scikit-learn in Python was used to implement XGBoost.

Table 4.3: Hyperparameters used for tuning the XGBoost model

Hyperparameters	**Values**
Maximum depth	{3, 4,………10}
Number of Estimators	{100, 101…….500}
Learning rate	{0, 1}
Lambda “L1” Regularization	{1, 2,……….6}
Alpha “L2” Regularization	{0, 1, 2, 3}
Subsample	0.8
ETA	0.1
Evaluation Metrics	RMSE and MAE

4.5.2. Feature Importance

The measurement of feature importance is often used to examine the features in the model that contributed to the model in ranked order of importance. Therefore, TreeExplainer and SHAP values were used to extract the feature importance from the test datasets. While determining the feature importance is crucial in supervised learning problems (i.e., regression and classification problems), it is only a portion of the process. It is often necessary to examine the relationship and interactions between the subsets of the identified essential features. The use of partial dependence helps to understand the marginal effect of a feature on the predicted target. It shows how the target outcome changes as the value of the important target changes while accounting for the average effect of all the other features in the model (Fredman, 2001; Liu et al., 2021, Lundberg et al., 2020). Therefore, SHAP dependence plots examined the interactions between different lead sources in residential homes.

4.6. Prediction Performance Measures

The implementation of the XGBoost model was used to predict blood lead levels (ug/dL). The prediction performance was evaluated by comparing the predicted BLLs with the measured BLLs using three measures of predict accuracy from the test datasets: the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). The smaller the RMSE and MAE, the better the model performance.

Mathematically, assume that y_i, ..., y_m are measured BLL for the parameter y, and $\hat{y}$ and $\hat{y}_m$ are the predicted BLL values. And $\bar{y}$ is the mean of measured BLL values.

1. The RMSE is defined as $RMSE = (\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2)^{\frac{1}{2}}$; (1)

2. The MAE is defined as $MAE = \frac{1}{m}\sum_{i=1}^{m} |y_i - \hat{y}_i|$; (2)

4.7. Results

The blood lead levels range from 0.3 to 222.5 µg/dL, with a geometric mean of 2.86 ± 3.82 µg/dL. Table 4.4 shows the geometric mean of blood lead levels per year of testing in Milwaukee County.

Table 4.4: The geometric mean of blood lead levels per year of testing

Year of Testing	Geometric mean ± Standard Deviation
2015	2.3 ± 3.6
2016	2.2 ± 3.7
2017	2.2 ± 3.8
2018	2.3 ± 4.2
2019	2.3 ± 4.1
Overall (2015 – 2019)	*2.9 ± 3.8*

4.7.1. Results of XGBoost

The tuning of the hyperparameters used on the training datasets with cross-validation using five-folds and 70 interactions resulted in the best parameters: maximum depth = 5; learning rate = 0.2 the number of estimators = 495; lambda "L1" regularization = 0.7; and lambda “L2” regularization = 4.1. The RMSE on the training and test sets are 3.4 and 4.1, which indicates that the training model performed better than the test sets. In addition, the mean absolute error on the training and test sets are 1.4 and 1.5. The lower the RMSE or MSE, the more accurate the predictive outcome of the model. In addition, the training model performed better than the test sets by a difference of 0.06. As a result, the result confirms that the model output is neither underfitting nor overfitting.

4.7.2. Feature importance

Figure 4.7 shows every feature's overall importance (i.e., global importance) to predicting BLLs. According to the model output and the absolute mean SHAP values of the test sets, the following features: the property value, building age, the property’s finished area, and soil lead concentrations are the most important features that contributed to predicting BLLs. On the other hand, physical housing features such as a fireplace, garage, cooling mechanism, and the finished basement area are the least important features of the model. In addition, lead service lines, which are a significant source of lead exposure, show weaker importance to the model than the building age and soil lead concentration.

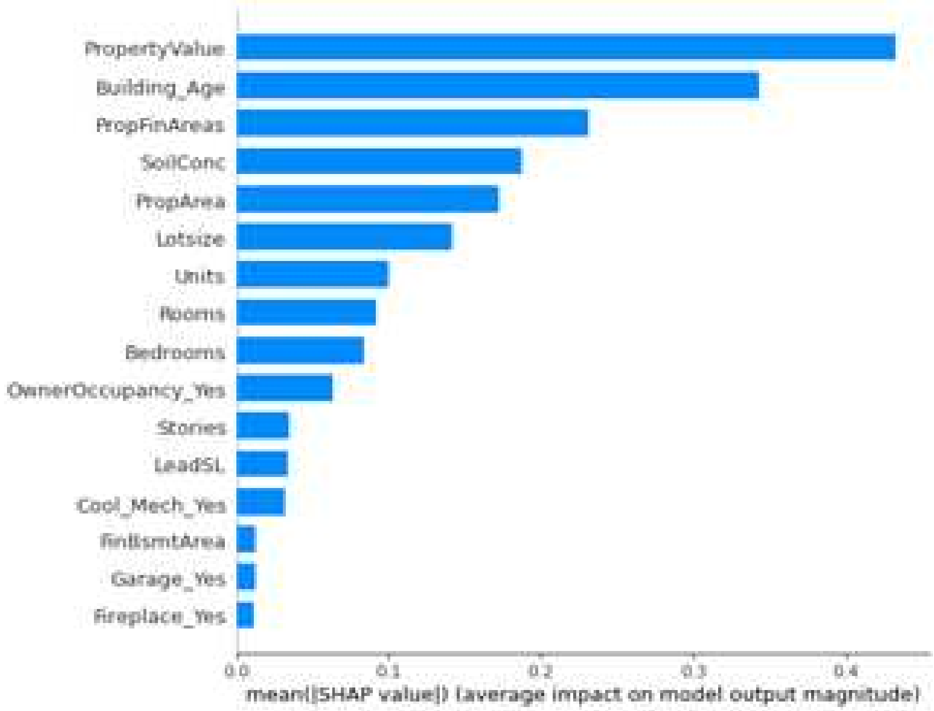

Figure 4.7. Figure showing the overall feature importance to predicting BLL values.

It is worth noting that the features with lesser contributions to the model (i.e., low mean SHAP value) might be a driving feature to predicting the BLLs for some specific children. Therefore, in order to obtain more information on the contributions of each feature and observation to the predicting BLLs, Figure 4.8 displays the magnitude, prevalence, and direction of each feature observation's contribution to the model. Each point corresponds to an instance of a single child. Thus, their position on the x-axis (i.e., actual SHAP value) shows whether the effect of that feature value caused a higher or lower BLL prediction for the specific child.

Meanwhile, the y-axis represents the mean of the feature's absolute Shapley values; the higher the feature is positioned in the plot, the more critical it is for the model (i.e., a higher position means higher importance). In addition, a child with a higher SHAP value has a higher blood lead risk relative to a child with a lower SHAP value. The plot (Figures 4.7 and 4.8) indicates that the lower property value is the most important feature contributing to the model's higher blood lead level risks. Thus, children living in houses with low property values could have higher blood lead level risks.

Living in older homes (i.e., higher building age) and living with high soil lead concentrations were both associated with increased BLL predictions. However, some children with low soil lead concentrations could also have higher blood lead level risks, possibly because their lead exposure from other sources is dominant (Figure 4.8). In addition, children whose lead service lines have been replaced with copper service lines could still be at higher blood lead level risks, potentially due to another dominant source of lead exposure in their residential homes. Furthermore, renter-occupied buildings have low feature importance (Figure 4.7), but local explanation shows that specific renter-occupied properties were associated with higher blood lead levels risks. However, to understand the interaction between varying levels of multiple exposures, we have to look at the SHAP dependence plots (Figure 4.9).

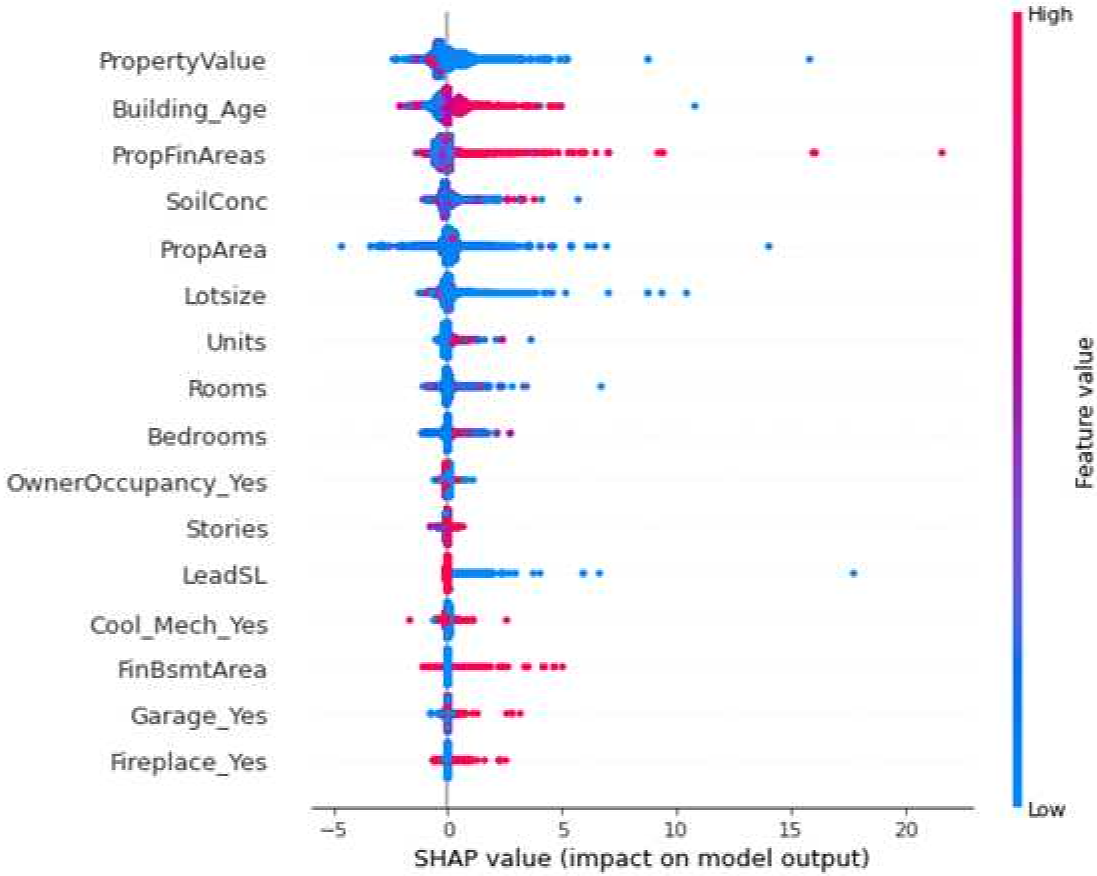

Figure 4.8: Summary plots for SHAP values. For each feature, one point corresponds to a single child. Thus, a point's position along the x-axis (i.e., the actual SHAP value) represents that feature's impact on the model's output for that specific child.

Using the SHAP interaction values plot, we can decompose the impacts of a feature on a specific sample into interaction effects with other features. Figure 4.9 shows the SHAP dependence plot indicating the interactions of specific features that answer this study's research questions. First, we examined the interaction between the age of homes and soil lead concentration (Figure 4.9a).

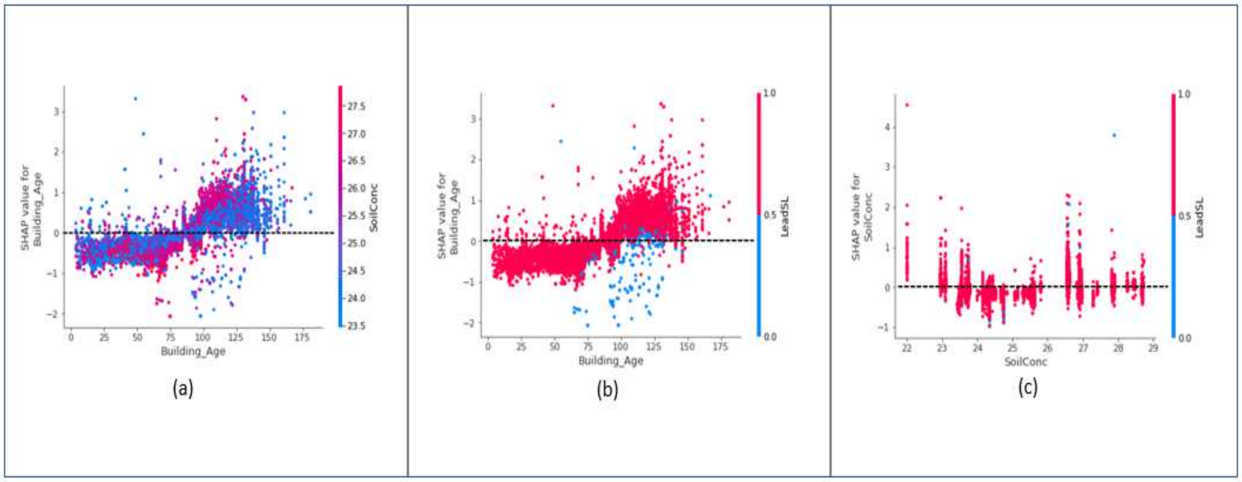

Figure 4.9: SHAP feature dependence plots showing the interaction effects of (a) building age and soil lead concentration (b) building age and lead service lines (c) soil lead concentration and lead service lines.

The SHAP interaction model indicates that a child who lives in an older building (above 85 years old) and is exposed to high soil lead concentration has a significant risk of blood lead level. Figure 4.9b shows the interaction between the building age and lead service lines. The plot indicates that the interaction of older homes (above 85 years old) served with water lead service lines is of significant concern in the model. That double source of lead exposure influenced higher blood lead level risks. Lastly, the model's interaction of soil lead concentration and lead service lines shows that children exposed to lead service lines and soil lead concentration (even at a low concentration) influenced the higher blood lead level risks. It is worth noting that this interaction is not a causal effect; instead, the plots indicate the combined effect after accounting for the individual feature effects in predicting BLLs.

4.8. Discussion

Our first research question focuses on the relative contributions of each source of exposure to blood lead levels among the children between the ages 1-5 living in Milwaukee County. Our XGBoost model aligns with prior studies that older buildings contribute significantly to pediatric lead poisoning risks in Milwaukee County than soil lead concentration and water lead service lines. This result does not indicate that older buildings are the primary source of exposure to all the children with blood lead levels. However, it mainly contributes to the positive blood lead levels in many children, especially those who live in homes above 85 years old in Milwaukee County. This result aligns with previous studies that reported significantly higher rates of pediatric lead poisoning in Milwaukee County are seen in part of communities with older housing stock (Christensen et al., 2020).

Our second research question focuses on the extent to which environmental exposure profiles interact synergistically to produce comparatively higher BLL outcomes for children in multiple exposures. The result shows that children residing in older homes above 85 years old and exposed to soil lead concentrations above 25 mg/kg could have higher blood lead level risks than children living in older homes alone or living where soil lead concentrations are high alone. It is worth noting that we were unable to determine whether these soils were undisturbed or garden soil lead concentrations due to the nature of the datasets. Furthermore, the interaction of building age and water lead service lines influenced the prediction of the BLLs. Thus, the combination of multiple exposures: living in older homes and being served with a lead-pipe water service line could be another significant driver of high pediatric lead poisoning in Milwaukee County. Children living in older homes above 85 years old but with replaced lead service lines (blue) have negative SHAP values, which indicates that the interaction of older homes and copper service lines could reduce the blood lead level risks. Since the city of Milwaukee is replacing the lead service lines in Milwaukee, the model output confirms that this approach could help reduce the high pediatric lead poisoning in the County, as shown in Figure 4.9b. This result is valuable for setting priorities of what households should rise to the top of a priority list for remediation. The corollary to this might also be that addressing even one of the two exposure pathways could significantly reduce child lead exposure.

Considering that a child might be exposed to multiple lead sources, it is critical to have predictive models to interpret the features and their interaction effects. Thus, the approach we took here provides new insights for identifying the influence of different sources of childhood lead poisoning in Milwaukee County. In addition, the use of SHAP values is an ideal choice for this analysis because it provides an insight into identifying different lead exposure patterns that could inform resource allocation needed to mitigate dominant routes of exposure in Milwaukee County.

The analyses of this study are limited in several ways. First, the soil samples were not collected in the years of testing, and they have a limited number of samples. However, the soil lead concentration does not degrade over decades, but further research should collect more representative soil samples. Moreover, the soil lead concentration should be collected in an undisturbed location (i.e., a location where the soil has not been turned over) so that it can help to have the background soil lead concentration across the study site. Also, the soil lead concentration calculated for individual subjects was estimated using a spatial interpolation tool in ArcGIS Pro, so the concentration might not reflect the true ground sample at the subject's home address.

Second, blood lead testing type could create a bias in the BLL values because the precision of the laboratory is critical in identifying any detectable lead exposure. In this study, our BLL values rely on three different tests methods: venous, capillary, and unknown methods. Some clinical practices rely on venous blood testing as a confirmatory test after a capillary blood point-of-care test. In this study, about 35% of the blood lead tests in Milwaukee county were from venous blood testing. Further studies should ensure that venous tests confirm higher positive pediatric lead poisoning, giving more reliable BLL values.

Lastly, our variables were collected at different times, which may cause inaccuracies and imprecision of the variables corresponding to a test result and further affect the model output. In this study, we used the blood tests results of children tested between 2015 – 2019, while the copper service lines data ranges from 2016-2019, and the soil lead samples were collected in 2006. Although the lead in the soil does not dissipate, biodegrade, or decay; however, it is worth noting that merging multiple data sources collected at different times could cause imprecision that could affect the model outcome. Our study successfully examined the cross-influence of multiple sources of lead exposure in a residential home that could contribute to blood lead level risks and inform how to channel the mitigation resources and policy enhancement towards reducing childhood lead exposures in Milwaukee county.

4.9. Conclusion

Our study findings showed that the interaction of older homes (above 85 years old) with copper lead service lines significantly reduces positive childhood blood lead levels in Milwaukee County. In addition, the model's interaction of soil lead concentration and lead service lines shows that children exposed to lead service lines and soil lead concentration (even at a low concentration) influenced the higher blood lead level risks.

Our results align with the results from prior studies that building age in many children contributed significantly to the BLL model prediction. Therefore, the Department of Housing and Urban Development's current mitigation efforts of re-painting existing lead paints with non-lead-based paints in old housing stock would be an appropriate intervention to avoid childhood exposure to lead in places like Milwaukee County.

There are so many children whose lead service lines might be driving their positive blood lead levels. Therefore, replacing lead service lines with copper tends to be an effective mitigation effort in reducing the risks of blood lead levels. Our study provides evidence that using machine learning-based such as XGBoost with SHAP values could provide insights into where and what mitigation efforts and actions would best mitigate pediatric childhood lead poisoning in Milwaukee County. In conclusion, our approach can be applied to investigate other environmental or geographical interactions (e.g., race, income level, and socioeconomic status) with blood lead level risks.

4.10. Acknowledgment

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CHAPTER FIVE

Evaluating Baseline Patterns of Indoor Environmental Exposures and their Determinants in Public Housing

5.1. Introduction

Indoor environmental exposures contribute substantially to the overall adverse environmental exposures and are likely driven by underlying racial and socioeconomic disparities in sources and indoor home environmental conditions (Lopez, 2002; Morello-Frosch and Jesdale 2006; Adamkiewicz et al. 2011). Poor indoor environment quality (IEQ) in homes can present significant health risks (Samet, 1993; Weisel et al., 2005; Logue et al., 2012), with some of the most vulnerable populations affected being children, seniors, and those with existing respiratory diseases (Peat et al., 1998; Emenius et al., 2004; Breysse et al., 2010). However, addressing indoor environmental exposures is challenging and complex because numerous indoor and outdoor sources and other socioeconomically patterned factors (e.g., dwelling size), housing quality, and neighborhood characteristics influence levels of exposure.

The home is an important source of environmental exposure. Residential indoor concentrations of airborne pollutants may be driven by the design and physical conditions of the home, use of mechanical ventilation system, air filtration pathways, household product use profiles, occupants' behavior, and infiltration of outdoor pollutants into the homes. Many studies have highlighted these factors as contributors to indoor environmental exposures, yet we still struggle to accurately estimate their relative contributions to indoor air and in-home exposures. It is essential to bridge this gap to identify where to best direct resources and efforts to intervene on exposures. Studies that characterize indoor air in various settings and under varying conditions are numerous. However, studies that determine sources and their contributions to indoor air or indoor exposures are much less common, limiting the evidence base needed to develop healthy home interventions and realize the home's potential as a place to reduce adverse exposures.

Source apportionment studies are much more common for outdoor air than indoor air. However, some examples of the application of these methods exist for indoor studies in different settings and locations (Brehmer et al., 2019; Dodson et al., 2017; Chu et al., 2021). For example, Chu et al. (2021) estimated indoor $PM_{2.5}$ concentrations of non-ambient origin using mass balance principles and investigated associations of indoor $PM_{2.5}$ with indoor source activities using mixed-effects quantile regression. The study found that the contributions from non-ambient sources (i.e., sources of indoor origin) to indoor $PM_{2.5}$ concentrations were higher among renters in multifamily housing than homeowners in single- and multi-family housing in the same study. Renters frequently reported cooking, smoking, spraying air freshener, second-hand smoke exposure, and living in units with higher air exchange rates and building density.

Furthermore, Dodson et al. (2017) examined and classified ~100 semivolatile organic compounds (SVOCs) and volatile organic compounds (VOCs) measured in 27 homes, based on occupant activities or building-related sources to examine the impact of renovation on indoor pollutants levels and to classify chemicals by predominant indoor sources. They showed that the building-related chemicals might be specific to particular housing development (e.g., dibutyl phthalate and xylene). However, the occupant-related chemicals (e.g., fragrance, cooking, smoking) might be generalized to similar communities. In addition, chemicals with known uses in personal care and cleaning products and those emitted from building and construction materials contribute strongly to indoor concentrations of volatile and semivolatile organic compounds. These studies heightened our understanding of how human activities, such as cooking and smoking (especially among renters), contribute to indoor air quality and vary seasonally, with indoor $PM_{2.5}$ concentrations, for example, being elevated during heating seasons. In general, reducing exposure to chemicals in the home environment would require multi-faceted approaches to acknowledge and address the many exposure sources, including home design, peoples' behaviors and activities in their homes, and transport of outdoor air pollutants across the building envelope.

Indoor air quality studies often reveal how variable indoor air composition can be between settings and households. Although some generalizations are possible, typically, studies that establish local baseline conditions are warranted, especially if changes to housing are to be thoroughly evaluated for their potential impacts on exposure and health. Public housing in the United States offers one such unique. However, yet untapped, opportunity to demonstrate whether changing peoples' homes have measurable impacts on harmful exposures, mainly because public housing policy has recently shifted toward comprehensive, place-based interventions. For example, the U.S. Housing and Urban Development agency's Choice Neighborhood Initiative involves diverse, multi-level changes, including area/neighborhood conditions, physical housing structures and interiors, and neighborhood socio-demographic and economic makeup. Rather than moving individual people out of distressed public housing (as was the case in past public housing models – e.g., Moving to Opportunity), the CNI approach favors redevelopment of existing communities and diversification of neighborhoods concerning class and race, with the idea that this will provide both health and social benefits to residents. Assessing the extent to which CNI and similar programs achieve their intended health and social benefits will be crucial to developing future housing policies. Nevertheless, CNI interventions have not been extensively evaluated.

Our objective for this initial baseline study was two-fold: (i) measure and characterize levels and distributions of particle and gas-phase pollutants in residential public housing; (ii) identify air pollution sources and their relative contributions to indoor air quality, using data from particle and gas-phase samples. To accomplish these two aims, we conducted week-long measurements of indoor air quality and household surveys in 38 public housing residences while they were occupied, as well as a subset of residences while they were unoccupied. We also conducted concurrent and identical measurements of outdoor air quality. The central hypothesis providing the basis for this work was that indoor activities would dominate sources of indoor pollution compared to the building-related emissions and outdoor sources. This work will contribute to establishing baseline indoor environmental conditions in public housing, slated for redevelopment, to support future longitudinal analyses of changes in housing quality, indoor air quality, and ultimately exposure and health outcomes associated with significant, wholesale replacement of housing.

5.2. Data and Methods

5.2.1. Study design and population

The study was conducted in two Denver Housing Authority residential complexes (Sun Valley and Quigg Newton). Eighty-three percent of households live below the poverty line, and the neighborhood's crime rate is 5.6 times the citywide average. In addition, the homes are townhouses (year built: 1950s) with similar layouts (e.g., number and arrangement of rooms; stories) and similar proximity to high-density motor vehicle traffic and traffic-related air pollution.

The field sampling took place in the spring and summer seasons (April – August 2021). Eligibility criteria for participation were that the study participant must be at least 18 years of age, currently residing in the DHA housing complex, and consent to in-home environmental sampling. Each home visit consisted of a detailed interview, a home visual assessment, and placement of real-time sensor platforms in the main living area (usually living room) to collect environmental samples for an average of seven days (range: 6-10 days). All participants involved in this study were provided informed consent and were compensated for their involvement. The Institutional Review Board of Colorado State University approved all study protocols used in this study (Protocol Approved: 21-10639H). Thirty-eight households were successfully recruited into and retained in the study. The recruitment exercise was performed randomly and based on participants' willingness to partake in the study.

Of the 38 units sampled, all but six were two-story, 2-5 bedrooms, with areas ranging from 750 – 1400 sq ft. All units were townhomes, and the household appliances were the same in all the units. For example, all households used gas stoves with similar recirculation fans. For heating and cooling, resident-controlled heaters were universal, and some households had and used window-unit air conditioners. However, there were no central air conditioners in any of the homes. Most (95%) respondents were adult females (25-75 years old). Twenty-nine percent of the participants have only adults living in the units, while others had at least one other adult or child residing in the units. Thirty-three percent of the units had at least one current smoker residing in the unit. Table 5.1 shows the characteristics of the study participants and housing units.

Measurements were collected to assess air and environmental quality in different settings: outdoors and indoors (both in occupied and unoccupied homes) over an averaging period of seven days per measurement. This sampling duration intends to capture most of the day-to-day variability in indoor activities and air pollution patterns that might be expected over a household's typical week. The indicators of indoor environmental quality that were measured include measures of particle-phase pollutant concentrations (e.g., fine particulate matter ($PM_{2.5}$), black carbon (BC)), gas-phase pollutant concentrations (e.g., carbon monoxide (CO), carbon dioxide (CO_2), oxides of nitrogen (NOx), volatile organic compounds (VOCs)), and hygrothermal conditions (e.g., temperature and relative humidity). The devices used for these measurements are described in Table 5.2.

Table 5.1: Characteristics of study participants and housing units

	n	%
Participant characteristics (n = 38)		
Age		
18-29	3	8
30-39	9	24
40-49	6	16
50-59	7	18
60-69	9	24
70-79	4	11
Gender		
Female	36	95
Male	2	5
Number of adults living in the unit		
1	11	29
2	14	37
3	13	34
Number of children living in the unit		
0	13	34
1	7	18
> 2	18	47
Total number of bedrooms		
1	5	13
> 1	33	87
Smokers in the unit		
Yes	13	35
No	25	65

5.2.2. Environmental sample collection

Briefly, we collected $PM_{2.5}$ mass using ultrasonic personal air samplers (UPAS), which sampled air actively and continuously at a rate of 1 L/min over a 37 mm filter (PTFE Teflo, 2 μm pore size, Pall Life Sciences, U.S.), on which particles with aerodynamic diameters of 2.5 μm or less were captured. In addition, passive sampling with thermal desorption tubes (SKC Inc., U.S.) and Ogawa samplers (PS-100, Ogawa, U.S.) was used to collect VOCs and NOx, respectively, over the sampling duration. All indoor samples (in occupied and unoccupied homes) were collected in a common room that was not the kitchen (i.e., the living room in all homes). Sample collection devices were placed approximately 1 meter above the floor and away from open doors or windows. In addition, identical outdoor environmental measurements were collected on the rooftop of one of the DHA buildings using similar measuring devices used for indoor sampling. Field blanks were collected for each sample type (e.g., filter, sorbent tube, Ogawa sampler) at a rate of ~10%, subject to the same field conditions as samples. After measurement, all filter samples and blanks were transported to the laboratory and stored in a -20°C freezer prior to mass and chemical composition analysis.

5.2.2.1. Environmental sample analyses

PTFE filters were conditioned for 24-h (21-22 °C, 30-34% relative humidity) and weighed in triplicate on a microbalance (Mettler Toledo Inc., XS3DU, USA) with a 1-μg resolution before and after sample collection. The average of three readings was used to determine filter mass before and after sample collection. The net mass (gross average minus tare average) was then blank-corrected using the mean value of blank filters.

Table 5.2: Description of devices used for measurement and the measured variables

Devices	Measured variables
Ultrasonic personal air sampler (UPAS)	Filter-based samples of $PM_{2.5}$ mass
Tsi Q-Trak 7565 indoor air quality monitor	Continuous (1-minute) concentrations of carbon dioxide (CO_2), carbon monoxide (CO), relative humidity (%), and temperature (F)
Tenax TA, steel thermal desorption tubes	Volatile Organic Compounds (VOCs)
Ogawa PS-100 passive samplers	Time-integrated concentrations of oxides of nitrogen (NO and NO_2)

Black carbon (BC) on PTFE filters was analyzed using an optical transmissometer data acquisition system (SootScan™ OT21 Optical Transmissometer; Magee Scientific, Berkeley, CA, USA). The classical Magee mass absorption cross-section of 16.6 m^2/g for the 880 nm channel was used to convert the light attenuation of BC on PTFE filters to mass surface loadings for further use in the ultimate calculation of BC concentrations. The mass surface loadings for black carbon were blank-corrected using the mean value of the blank filters.

Elemental analysis of filter-based $PM_{2.5}$ mass was performed using a Thermo Scientific Quant'X Evo energy-dispersive X-ray fluorescence (EDXRF) spectrometer with Wintrace software version 10.3. Quantitative mass concentrations of 12 individual elements (Si, Al, Ca, Mg, Ti, S, Fe, Zn, Pb, Se, Cr, Cu) were determined empirically using linear-standard curves. Standard curves were generated from a commercial, single and dual element, thin-film standards from MicroMatter, Technologies Inc. (Montreal, Canada) in addition to blank films. In addition, the quality of the analysis method was evaluated by analyzing a National Institute of Standards and Technology (NIST) standard reference material (SRM) 2783 Air particulate on filter media (Gaithersburg, MD, USA).

All particle-based concentrations (i.e., $PM_{2.5}$ mass, black carbon, metals) were determined by dividing the blank-corrected mass measured on the filter by the corresponding total volume of sampled air. In the case of black carbon and metals, the surface loadings were first multiplied by the sampled filter area. Next, the total sampled air volume was determined from the UPAS, which continuously records the sampling flow rate during sample collection. The UPAS maintains a constant sampling flow rate, calibrated prior to each sample run with a primary flow standard (MWB-5SLPM-D/Gas; Alicat Scientific Inc., U.S.) and verified at the end of each sample run. Post-sampling flow rates did not vary by more than 2% of pre-sampling flow rates. All filter-based particle samples achieved at least 80% of the target sampling time and thus, no samples were dropped for incompleteness.

We collected VOCs, including formaldehyde and acetaldehyde, using commercially available thermal desorption (TD) tubes packed with Tenax TA (Catalog No. C1-AXXX-5003, Markes International, Llantrisant, UK) and samplers (UMEx, 100, SKC Inc., U.S) designed for passive sampling. The thermal desorption tube and UMEx 100 samples were analyzed at the University of Memphis using gas chromatography with mass spectrometry (GC-MS) and high-performance liquid chromatography (HPLC). The GC-MS method was designed to identify and quantify (when possible) 48 compounds. The Supporting Information (supplementary material A1) provides a complete list of analytes.

All VOC samples were analyzed following the same analytical procedure. In the laboratory, tubes were thermally desorbed on an automated TD system (ULTRA 2 + UNITY 2, Markes International, Llantrisant, UK) coupled to a gas chromatography/mass spectrometry system (GC/MS, Agilent 7890A/5975C, Agilent, Santa Clara, CA, USA). A prior study described the analytical conditions and parameters in detail (Jia and Fu, 2017). The collected chromatograms were identified and quantitated for 70 target compounds in ChemStation (version F.01.03.2357), but 64 were detected in DHA homes. Method detection limits (MDLs) were 0.04 − 0.32 μg/m3 for 2 L active samples and 0.01 − 0.05 μg/m3 for a 7-day passive sample.

Integrated NO and NO_2 were measured using Ogawa passive diffusion samplers (Ogawa USA; Pompano Beach, FL, USA) and chemically treated sample collection pads. Post-measurement, the collection pads were stored in distilled/de-ionized water for subsequent laboratory spectrophotometric analysis (Ogawa & Co., USA, Inc., 2014) at the Environmental Health and Radiological Sciences Department, Colorado State University. Analysis of two separate sample collection pads yields concentrations for combined NOx species and NO_2 (ppb), respectively. The difference between the two is the NO concentration (ppb). The TSI Q-Trak 7565 air quality monitor was used to measure the real-time amount of CO, CO_2, temperature, and relative humidity, in the residential unit. All measured data were logged and averaged at a 1-minute interval for analysis.

5.2.3. Survey measurements

The survey for this study was adapted from previously validated questionnaires (Rosofsky et al., 2019; Chu et al., 2021). The survey development was also informed by a holistic conceptual model (Swope and Hernandez, 2019) that posits four key pathways, including cost (housing affordability), conditions (housing quality), consistency (residential stability), and context (neighborhood opportunity), through which housing shapes health. Specifically, the questionnaire administered by a trained team member focused on housing conditions: building characteristics, heating, and cooling systems, ventilation, safety, residents' rating of their dwelling, time-activity patterns, household cleaning practices, and sleeping patterns. A copy of the questionnaire is provided in supplemental material A2.

5.3. Data Analysis for Air Pollution Source Identification

Eight elements (Ca, Cu, Fe, K, Mg, S, Ti, Zn) measured by X-ray fluorescence (XRF) were detected and quantified after correcting for the field blank means in > 75% of homes and were included in the source analysis. Crustal enrichment factors (CEFs) were calculated to identify elements that had been anthropogenically enriched by comparing the relative concentration of an element in the sample to a reference element (iron in this study) to the same relative concentration in the earth's crust (Secrest et al., 2016). A CEF less than 10 indicates the element is likely of crustal origin, whereas a CEF greater than or equal to 10 suggests the element originates from an anthropogenic source. These eight (8) elements were also included in a principal component analysis (PCA) with varimax rotation to identify their potential sources in our samples.

We also performed a similar PCA on the VOC compounds. We excluded VOCs that were not measured in at least 75% of the households, resulting in 48 VOC compounds detected in DHA homes. The PCA is performed with variables standardized to a mean of 0 and a standard deviation of 1. We selected the top five principal components which retain the eigenvalues of at least 1.0 and a minimum loading score of 0.30. The five components explain 50% of the total variance of the detected indoor VOC compounds. The first principal component (PC1), which is the largest variance, explained 20% of the dataset, while the principal component PC2, PC3, PC4, and PC5 explained 12%, 7%, 7%, and 5% of the datasets, respectively.

5.4. Results

5.4.1. Household Sources and Activities Associated with Air Quality

Table 5.3 summarizes the household cleaning practices of the study participants. Sweeping and dusting are the most consistent cleaning activity. Sixty percent of the households sweep daily, while sixty-six percent dust or mop their homes every week. In addition, figure 5.1 summarizes the usage of household cleaning products (as a percentage of homes reporting using each product). Toilet cleaners, bleach, and spray air fresheners were the most widely used products, with reported usage in 35%, 34%, and 29% of homes, respectively.

Table 5.3: Summary of the household cleaning practices of the study participants

Sweeping	**Daily (%)**	**Weekly (%)**	**A few days per week (%)**	**Never (%)**
Sweep	60	37	0	3
Vacuum	18	41	6	12
Dust	6	66	26	3
Mop	26	66	9	0

5.4.2. Descriptive Statistics of Indoor Environmental Quality Indicators

5.4.2.1. Particulate Matter

In this study, most of the measured indoor environmental and air quality indicators were log-normally distributed; therefore, we took the median to represent central tendency in DHA homes. The median indoor $PM_{2.5}$ concentration in DHA-occupied homes was 11.9 µg/m^3 (IQR = 13.9 µg/m^3) (Table 5.4). We found that the median indoor $PM_{2.5}$ levels measured in DHA homes were lower than the median indoor $PM_{2.5}$ concentrations reported in other studies of similar residences in the United States. For example, Colton et al. (2014) reported a median of 15.1 µg/m^3, and Frey et al. (2015) reported a median of 13 µg/m^3. Coombs et al. (2016) reported a median of 41 µg/m^3 in similar low-income homes in Ohio (Figure 5.2).

Furthermore, we measured the indoor $PM_{2.5}$ concentration in unoccupied homes to understand the background concentration in DHA homes (median = 10.7 µg/m^3; IQR = 3.2 µg/m^3). The unoccupied median $PM_{2.5}$ concentration was subtracted from the occupied concentration (assumed as background measurement in this context) to estimate the contribution of occupants' activities to indoor PM. The occupants' activities contributed a median indoor concentration of 8.2 µg/m^3, indicating occupants and their activities may have contributed 60-69% of the $PM_{2.5}$ mass in DHA homes, slightly lower than the 77% contribution reported in similar multifamily public homes in the Boston area (Chu et al., 2021).

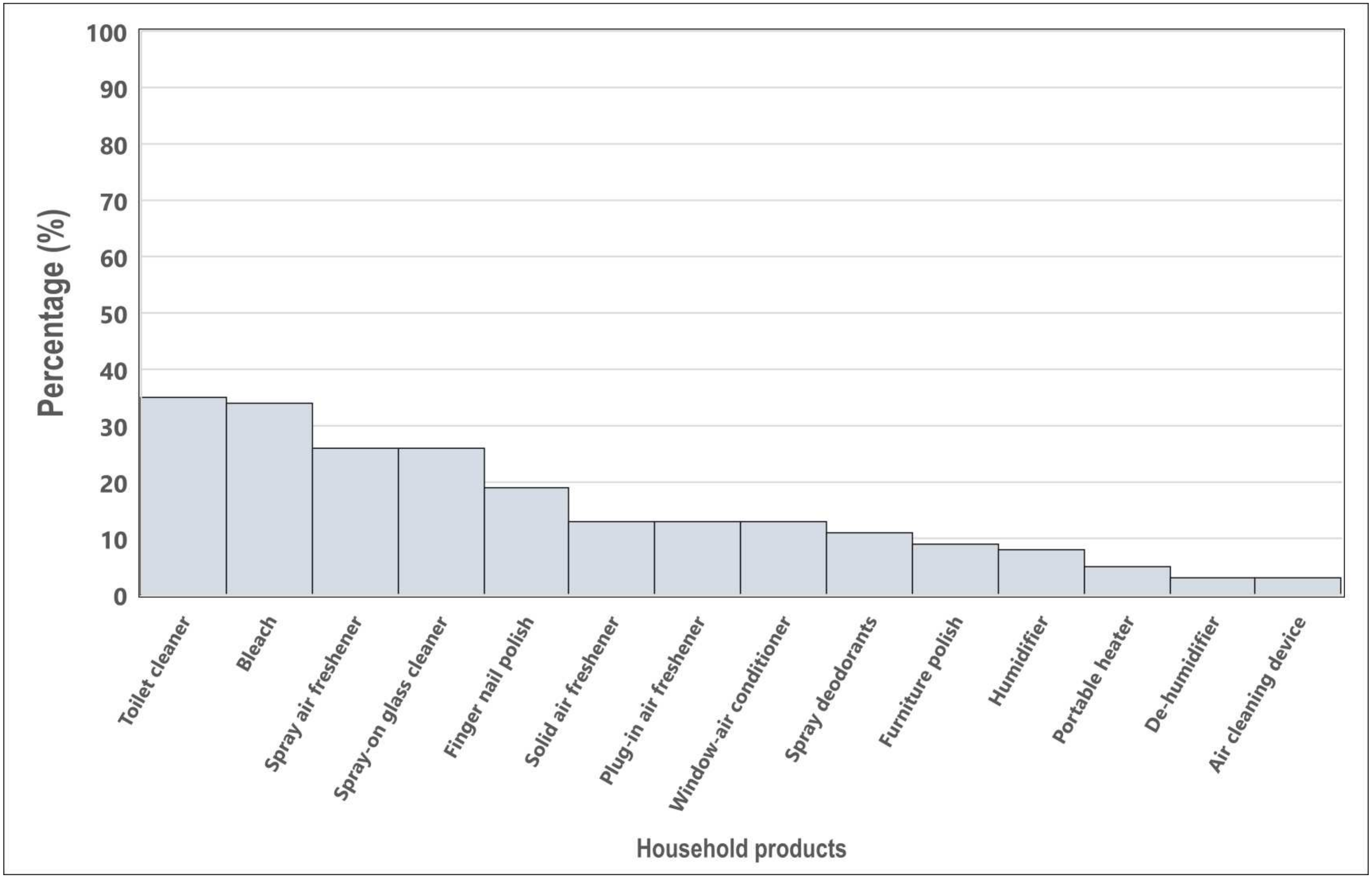

Figure 5.1: Summary of household cleaning product usage

In addition, the median concentration of indoor $PM_{2.5}$ was higher than the median outdoor concentration of 8.3 µg/m^3 (IQR = 2.9) µg/m^3. Therefore, to take a first step toward understanding the contribution of outdoor PM to indoor PM, we evaluated the ratio of indoor to outdoor $PM_{2.5}$ concentrations (I/O) (Figure 5.3). While this approach cannot directly distinguish between indoor PM generated indoors versus indoor PM of outdoor origin, indoor-to-outdoor ratios can provide insight into how enriched the indoor environment is in a given pollutant (in this case, $PM_{2.5}$) relative to the local outdoor environment. For example, if indoor to outdoor ratios of a given pollutant (in this case, $PM_{2.5}$) are greater than 1, as our results show in this study, we infer that indoor PM sources contribute to indoor PM more than the contributions made by PM of outdoor origin. In future work, we will analyze several known tracers of outdoor PM to estimate contributions of outdoor PM more precisely to indoor PM overall.

Table 5.4: Summary statistics of PM2.5 measured in DHA homes (occupied units, n = 38 and unoccupied units, n = 6)

(µg/m^3)	Median	Interquartile Range (IQR)	Mean	Standard Deviation
DHA Occupied	11.9	13.9	25.9	4.1
DHA Unoccupied	10.7	3.3	3.3	6.1
Estimated contribution of DHA occupants' activity	8.2		22.6	
Other U.S. studies (n=13)	15.7			
Outdoor	8.3	2.9	8.9	7.2

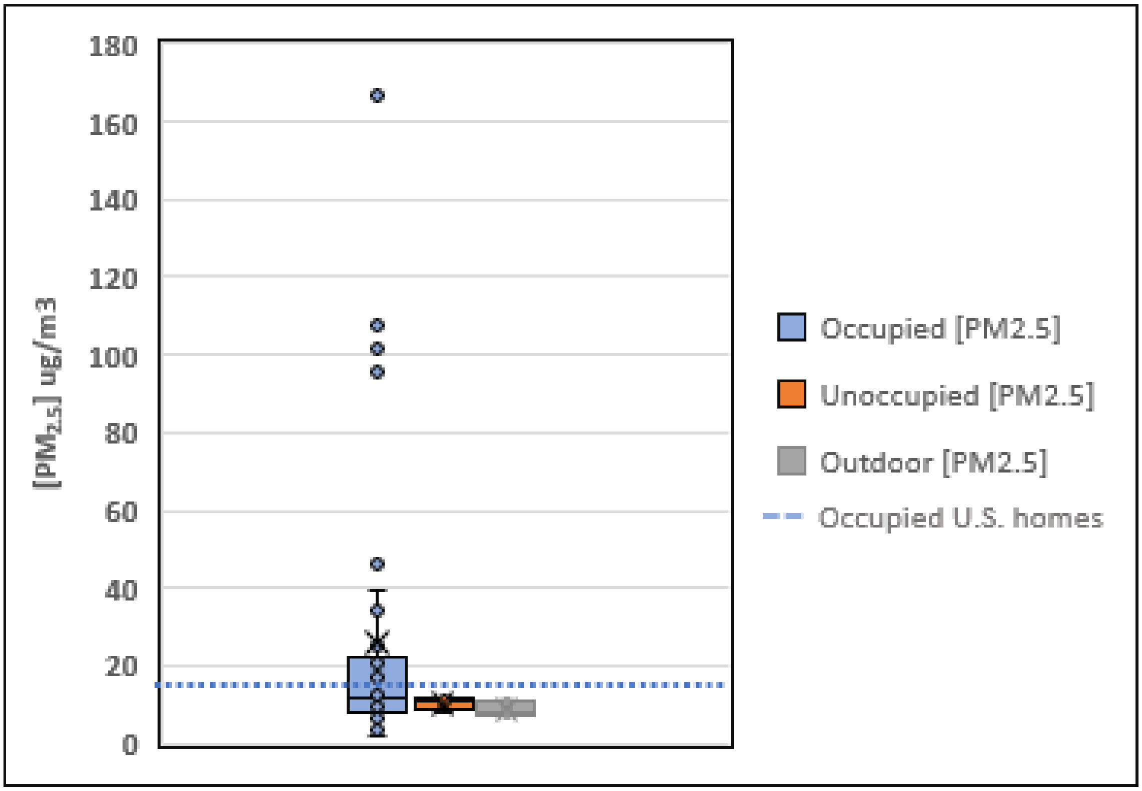

Figure 5.2: The range of $PM_{2.5}$ measured in occupied (n=38), unoccupied units (n=6), and outdoor (n=6) in DHA apartment complexes.

5.4.2.2. Black Carbon

Indoor black carbon, as a percent of indoor PM mass, ranged from 0.1 – 5.1%, with median concentrations of 1.3 (IQR = 1.1 μg/m^3) and 1.1 (IQR = 0.24 μg/m^3) (Figure 5.4) in occupied and unoccupied homes, respectively. By comparison, outdoor BC concentrations was only slightly higher (median: 1.6 μg/m^3 and IQR = 0.73 μg/m^3). Given that there are few known indoor sources of black carbon, our results suggest that a dominant source of indoor BC is outdoor BC, which may

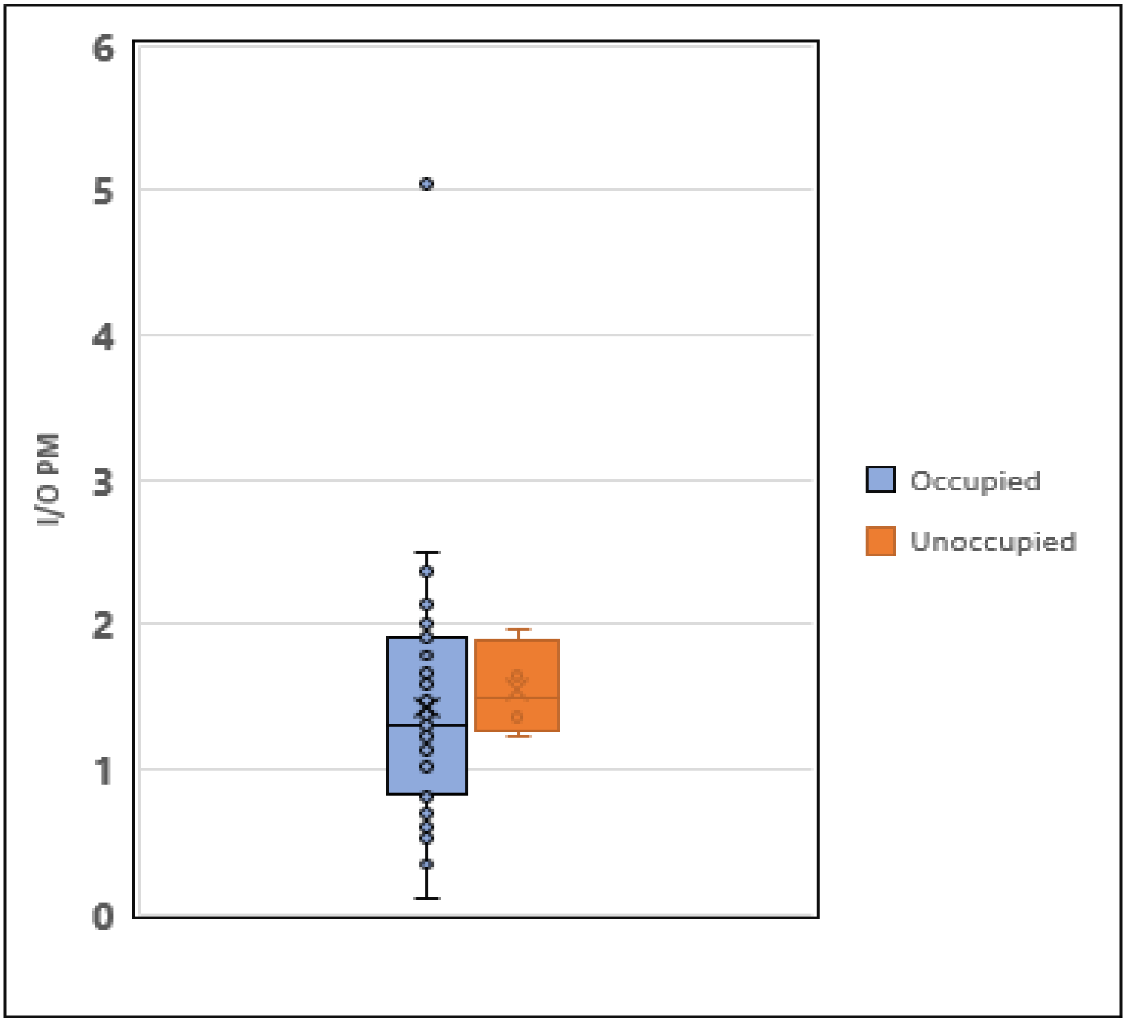

Figure 5.3: The ratio of indoor to outdoor $PM_{2.5}$, where indoor $PM_{2.5}$ is measured separately in occupied (n=38) and unoccupied units (n=6) in DHA apartment complexes.

infiltrate through the building envelope and impact indoor air quality in DHA homes. Black carbon is emitted from combustion activities, including gasoline-powered vehicles proximal to DHA homes.

Table 5.5: Summary statistics of BC measured in DHA homes (occupied units, n = 38, unoccupied units, n = 6, and outdoor n = 6)

Black Carbon (BC)	**Median (µg/m^3)**	**Interquartile Range (IQR)**	**Mean**	**Standard Deviation**
Occupied	1.3	1.0	1.4	0.9
Unoccupied	1.1	0.2	1.3	0.6
Outdoor	1.6	0.7	1.6	0.7

5.4.2.3. The oxides of Nitrogen

The indoor NO_2 and NO concentrations in occupied homes ranged from 2.6 – 363.4 and 48 – 128.7 ppb, respectively (Table 5.6), with median concentrations of 13.7 (IQR = 10.2) ppb and 15.3 (IQR = 20.8) ppb (Figure 5.5), respectively. These indoor NO_2 concentrations were 1.3 times higher than in unoccupied homes and two times higher than outdoor NO_2 concentrations. Similarly, indoor NO concentrations in occupied homes were 2.1 times higher than in unoccupied homes and 1.9 times higher than outdoor NO_2 concentrations. Thus, elevated concentrations of NO_2 indoors likely reflect the contribution of both indoor (i.e., cooking with gas) and outdoor (i.e., gasoline-powered vehicles) sources.

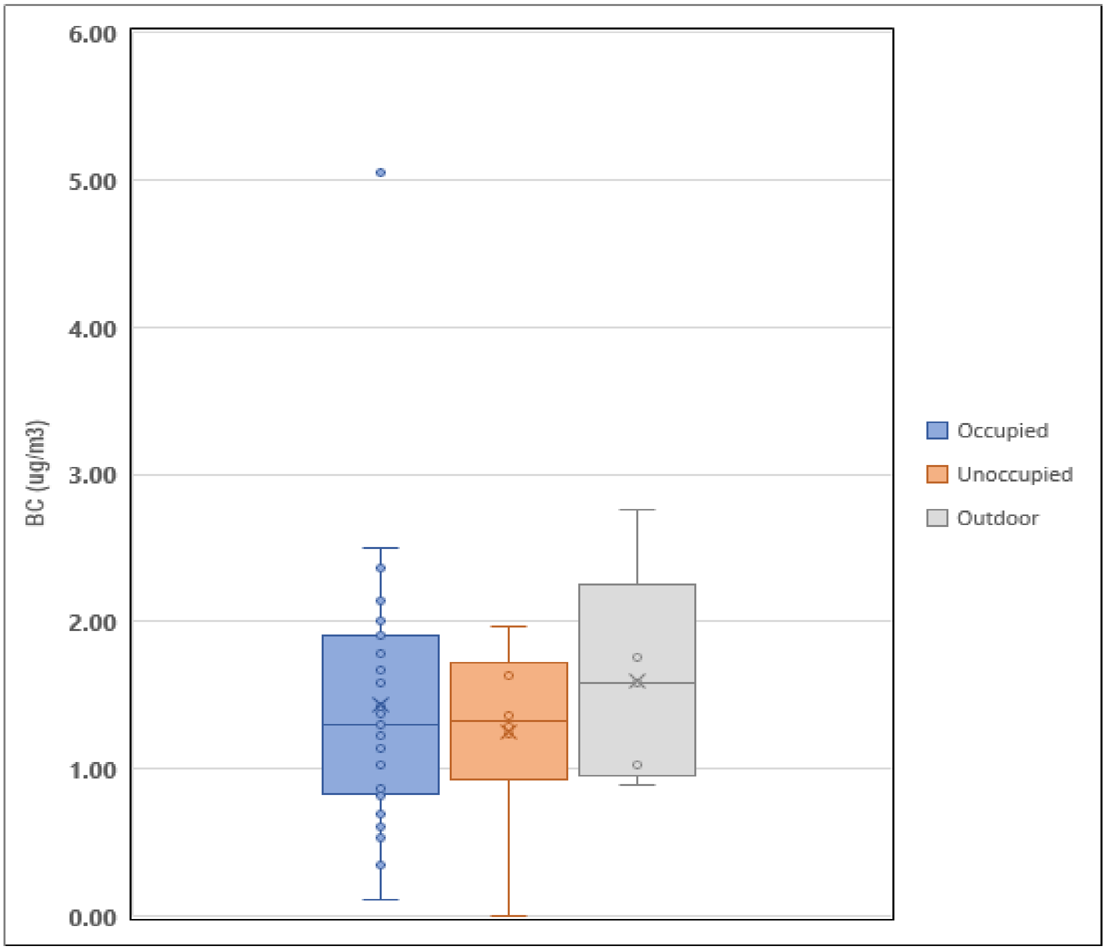

Figure 5.4: The range of BC measured in occupied (n=38) and unoccupied units (n=6) in DHA apartment complexes

5.4.2.4. Other indicators of indoor environmental quality

The result of other indicators of indoor environmental quality over a 24-h average for CO_2, CO, temperature, and relative humidity are shown in table 5.7. The median concentration of indoor CO_2 and CO were 624 (IQR = 336.0) ppm and 0.1 (IQR = 0.9) ppm, respectively. The median indoor temperature was 76.8 (IQR = 10.4) F, while the median relative humidity was 37.1 (IQR = 6.8)%. In contrast, the median unoccupied temperature was 83.1 (IQR = 1.8) F, and the median relative humidity was 37.1 (IQR = 6.8) %.

Table 5.6: Summary statistics of NO_2 and NO measured in DHA homes (occupied units, n = 38 and unoccupied units, n = 6)

Pollutants	Median (ppb)	Interquartile Range (IQR)	Mean (ppb)	Standard Deviation
Occupied				
NO_2	13.7	10.2	26.9	57.3
NO	15.3	20.8	29.2	33.3
Unoccupied				
NO_2	9.8	3.7	11.6	4.8
NO	7.1	5.8	9.2	3.9
Outdoor				
NO_2	8.6	5.6	8.8	3.5
NO	9.9	6.1	9.9	3.9

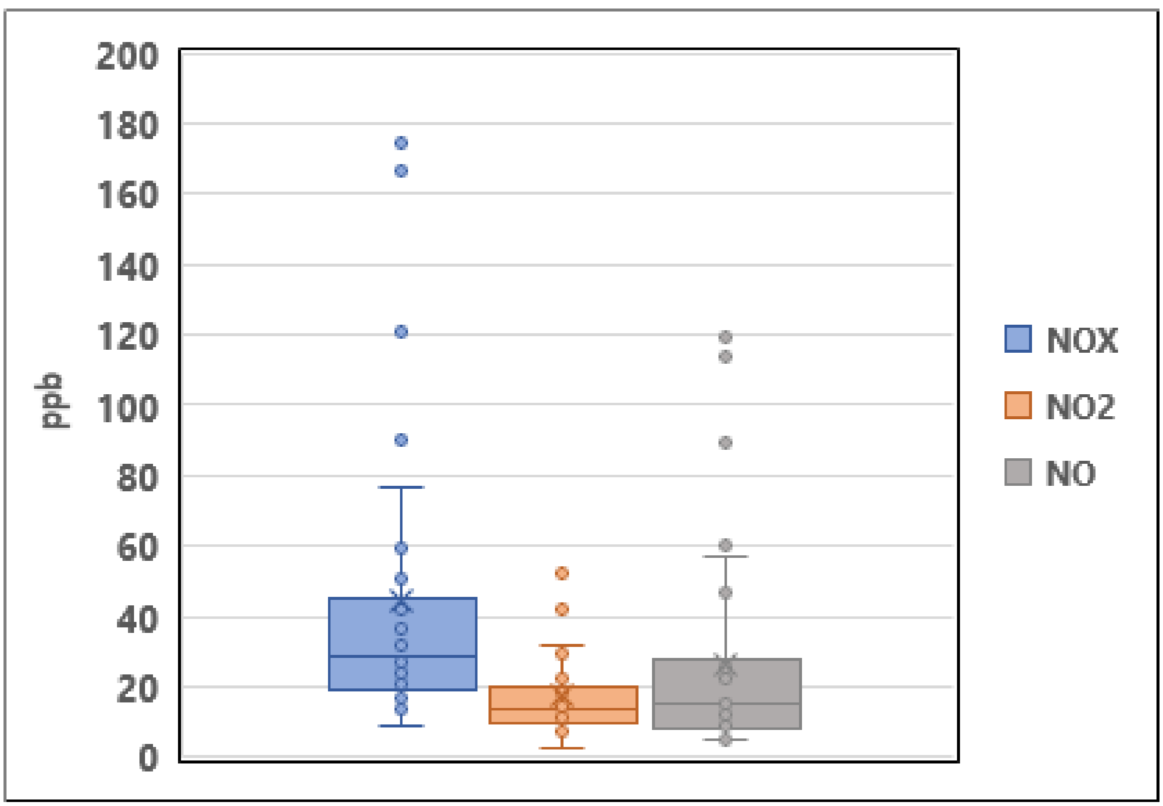

Figure 5.5: The range of NO_x, NO_2, and NO measured in DHA-occupied homes (n=38). The household with the highest values was not included in the plot because of the y-axis scale [NOx, NO_2, and NO: (492, 363, 129) ppb].

Table 5.7: Summary statistics of other IEQ measured in DHA homes (occupied units, n = 38 and unoccupied units, n = 6)

Pollutants	Median	Interquartile Range (IQR)	Mean	Standard Deviation
Occupied				
CO_2 (ppm)	624.0	336.0	735.0	265.0
CO (ppm)	0.1	0.9	18.9	62.9
Temp (F)	76.8	10.4	77.8	6.5
RH (%)	39.9	6.8	37.1	7.2
Unoccupied				
CO_2 (ppm)	491.0	148.0	431.0	101.0
CO (ppm)	1.1	33.1	28.3	41.6
Temp (F)	83.1	1.8	81.1	6.5
RH (%)	36.6	1.2	36.8	7.2

5.4.2.5. Volatile Organic Compounds

In total, our analysis methods for volatile organic compounds were optimized for a standard, and a common set of 48 compounds (Table S1), all of which are Hazardous Air Pollutants (HAPs), whose emissions are regulated by the U.S. Environmental Protection Agency. We detected and quantified multiple compounds with at least one hydroxyl functional group (-OH) (e.g., isopropyl alcohol, ethyl alcohol, 2-ethyl-1-hexanol, 2-Butoxyethanol) in every DHA home. Their representative (Figure 5.6) and upper-bound concentrations (Figure 5.7) range from 1-3 orders of magnitude. Likely sources of these VOCs are found in household and cleaning products.

In addition, the aldehyde functional group (H-C=O), which includes formaldehyde and acetaldehyde, was commonly found in DHA homes. Building materials and household products are familiar sources of these pollutants in residential units. The formaldehyde concentrations ranged from 4.4 – 53.3 μg/m^3, with a median concentration and upper-bound concentration of 14.7 and 40.5 μg/m^3, respectively. The acetaldehyde concentrations ranged from 0.8 – 14.5 μg/m^3, with a median concentration and upper-bound concentration of 4.6 and 12.7 μg/m^3, respectively. The most common VOCs in occupied homes were also common in unoccupied homes but with lower concentrations (Figure 5.8). We estimated the difference between the representative mid-range concentrations between both units. (See supplemental material -Table A1). The median representative concentration of ethyl-alcohol and ethyl acetate increased significantly in occupied homes compared to unoccupied homes, possibly indicating occupant's activity (i.e., the use of household cleaning products and fragrances).

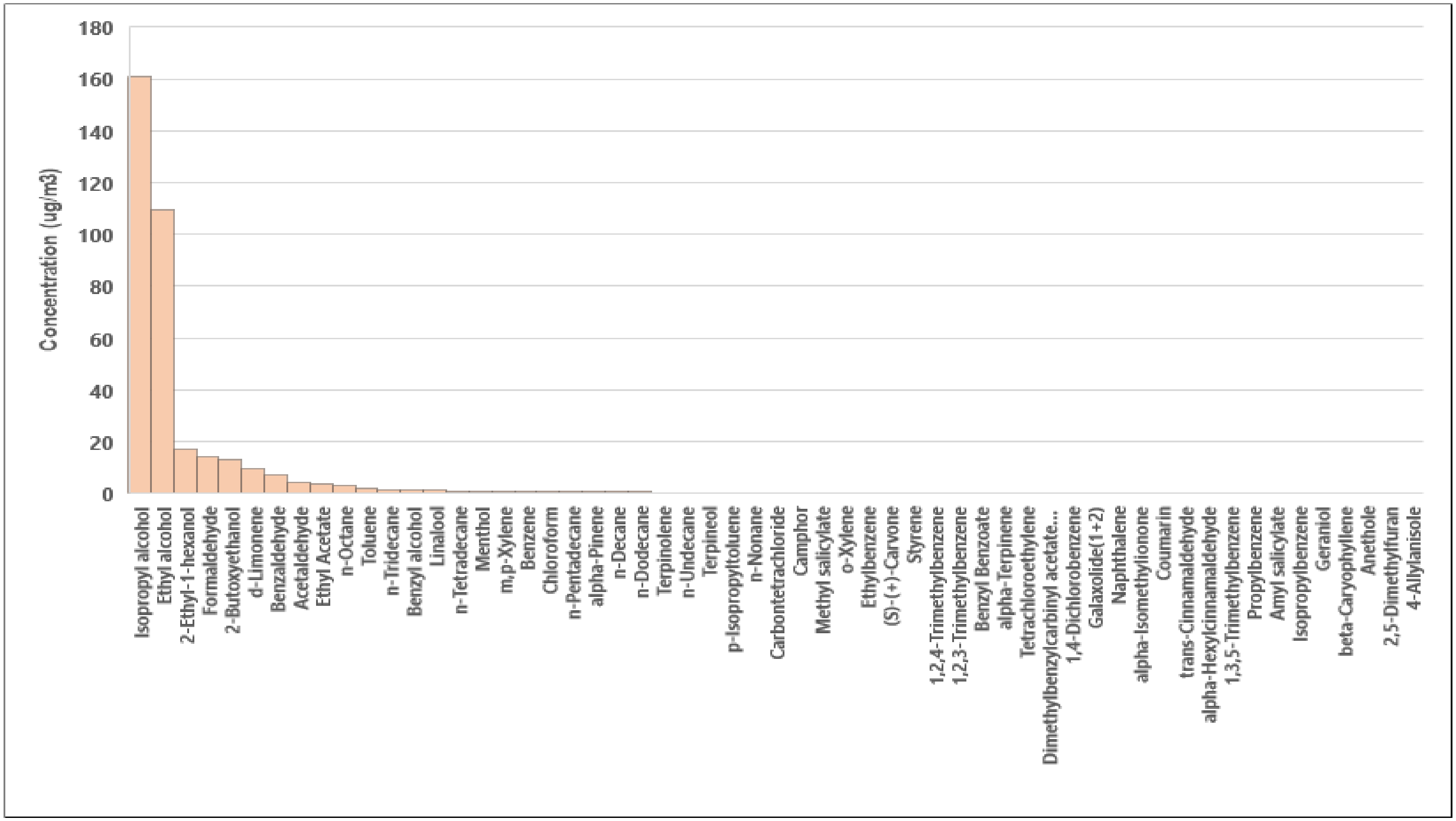

Figure 5.6: Representative mid-range (median) indoor air concentrations of VOCs measured in DHA-occupied units (n=38)

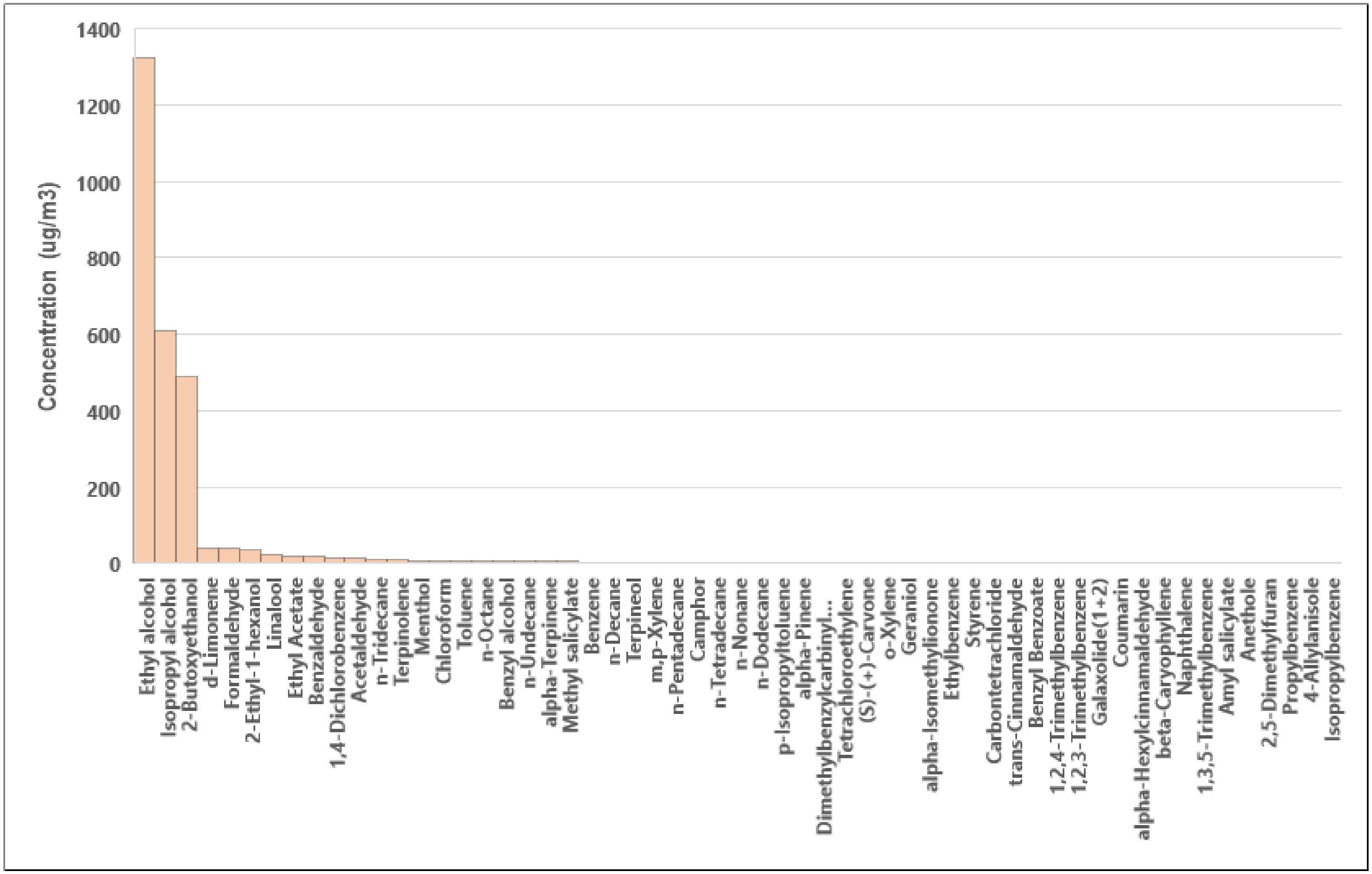

Figure 5.7: Representative upper-bounds (95th percentile) of indoor air concentrations of VOCs measured in DHA-occupied units (n=38)

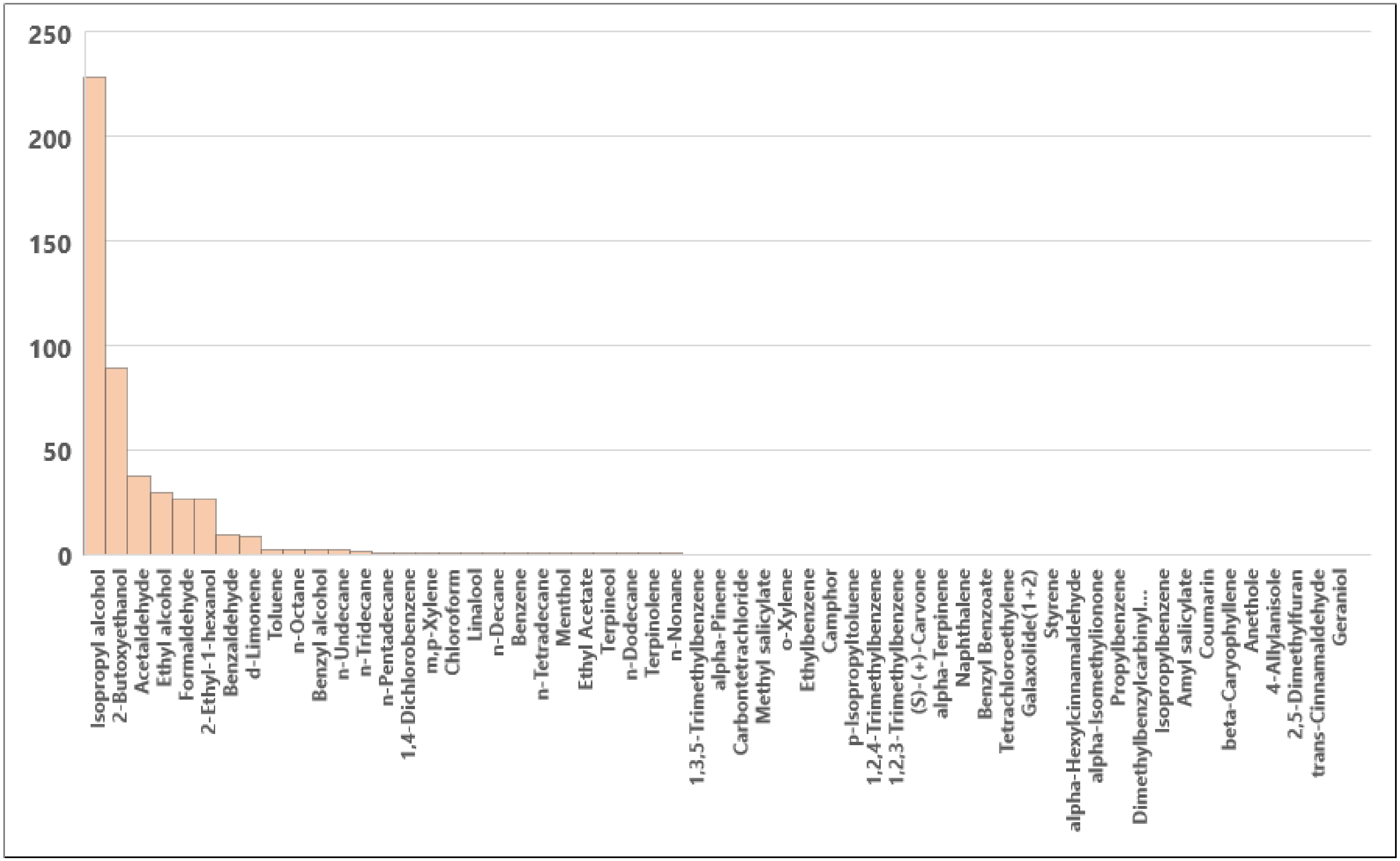

Figure 5.8: Representative mid-range (median) indoor air concentrations of VOCs measured in DHA-unoccupied units (n=6)

5.4.3. Potential health hazards from selected indoor and environmental exposures.

This section compared the representative indoor air concentrations to the relevant standards for health hazards. The bar indicates the representative mid-range concentration, extending to the representative upper-bound concentrations in all the figures.

Figure 5.9 shows representative indoor concentrations of criteria pollutants compared with relevant national and international health standards: the United States Environmental Protection Agency (USEPA) - National Ambient Air Quality Standards (NAAQS), and World Health Organization (WHO). The representative upper bound concentration for $PM_{2.5}$ is above both the NAAQS and WHO 24-h and annual standards. The representative upper bound concentration for NO_2 is above WHO annual standards but below the WHO and NAAQS 24-h standards. Thus, in some homes, the $PM_{2.5}$ and NO_2 concentrations averaged over periods of seven days can exceed both the chronic and short-term acute health standards. In contrast, the CO concentrations in DHA homes did not exceed any of the standards (See Tables S2 and S3 for the national standards).

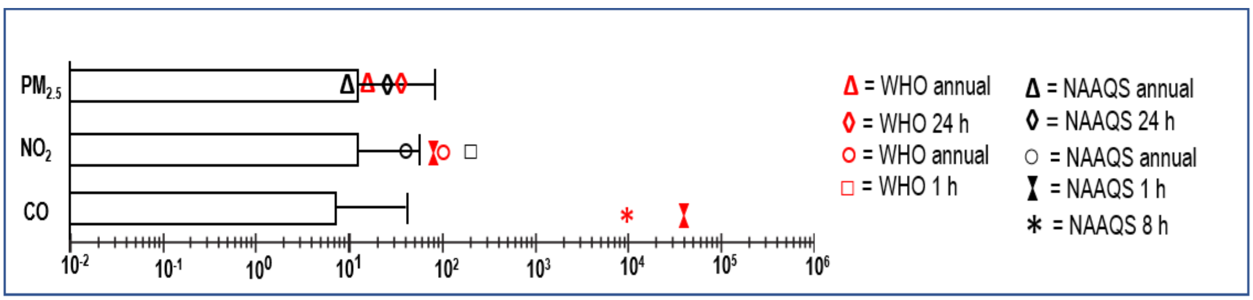

Figure 5.9: Selected representative indoor air concentrations compared to relevant national and international standards. Error bars extend to the upper-bound representative indoor concentrations.

Hundreds of VOC compounds could be detected in indoor environments, but not all are harmful to human health. Specifically in this study, we focused on the VOCs that have been identified and reported as priority hazards in a prior comprehensive study review of 200 VOC compounds based on robustness and measured concentrations and fraction of residences that appeared to be impacted in the US housing stock (Logue et al., 2011). In addition, the selected VOC compounds were classified as either associated with chronic or acute health hazards. As a result, we identified 13 VOC compounds that have been identified as pollutants that could potentially pose an adverse indoor health risk (Figure 5.12). Eleven (11) VOCs could pose chronic health hazards, while two (2) VOCs, chloroforms and formaldehyde, could cause acute health hazards. Furthermore, we compared the identified priority hazards with common national health standards: the California Environmental Protection Agency (CALEPA), Occupational Safety and Health Administration, and United States Environmental Protection Agency (USEPA).

Briefly, the USEPA has listed chronic noncancer reference concentrations (*RfCs*) and cancer unit risk estimates (UREs) through the Integrated Risk Information System (IRIS) and Health Effects Assessment Summary Tables (HEAST). UREs estimate the incremental increase in cancer risk for each one $\mu g/m^3$ increase in chronic exposure. Noncancer *RfCs* report the exposure concentrations assumed to represent a safe level. Therefore, they are unlikely to cause health effects even for sensitive population subgroups. In addition, the California Office of Environmental Health Hazard Assessment (OEHHA) publishes noncancer reference exposure levels (RELs) and cancer UREs. In addition to the California and USEPA values, the US Occupational Safety and Health Administration (OSHA) sets reference concentrations for workplace exposures, and the

Toxic Substances and Disease Registry publishes RfCs for chronic exposure. Lastly, the OSHA regulations are intended to protect generally healthy adult workers. Therefore, their allowable concentrations tend to be higher than those set for "air toxics" by the USEPA and CalEPA (Logue et al., 2011).

Figure 5.10 shows that the upper bound concentrations of benzene, acetaldehyde, naphthalene, and 1,4-dichlorobenzene exceed the CalEPA REL. The result indicates that many DHA households over seven days averaging period were exposed to a concentration of these VOCs that exceeds chronic health hazards. In addition, the representative mid-range concentration of formaldehyde exceeds the EPA noncancer *RfCs*, and CalEPA cancer *REL*. Also, the upper-bound concentration of chloroform was above the EPA cancer UREs. This pattern indicates that many DHA homes are exposed to concentrations of formaldehyde and chloroforms that exceed acute health standards.

5.4.4. Source Analysis – Particle-phase pollutants

Crustal enrichment factors are shown in Figure 5.11, and factor loadings for the principal component analysis are given in Figure 5.12. Factor 1 (the top panel) was characterized by high factor loadings for Magnesium, Calcium, and Sulfur. While the low median CEF of Mg (1.25) and Ca (2.39) may suggest a crustal origin for this source, Sulphur had the second-highest median CEF of 47.3, which indicated that this was likely an anthropogenic source. Sulfur is a common tracer for sulfurous fuel combustion, such as coal, that emits gaseous SO_2, which is oxidized in the atmosphere to form particulate SO_4^{-2}.

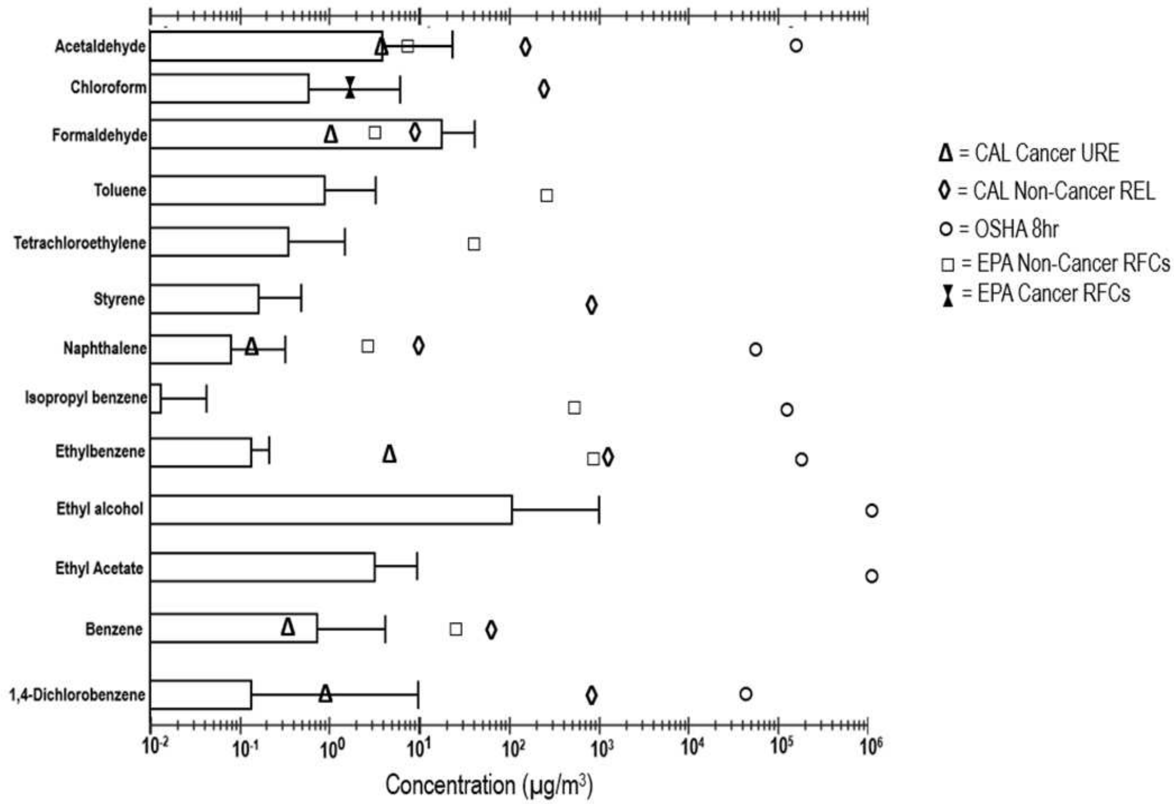

Figure 5.10: Representative indoor air concentrations in DHA-occupied homes (n=38) compared with national and international standards. Error bars extend to the upper-bound representative indoor concentrations. Cancer, *RfC,* and REL standards are for chronic long-term exposure (70 years).

Since several sources could contribute to this factor, including coal combustion, traffic, and other sulfurous fuel sources, this source was named "regional aerosol" (Pekney et al., 2006). The second factor had high factor loadings for Ti and Cu, both associated with vehicle and brake pad abrasion (Thorpe and Harrison, 2008). Copper had the highest median CEF of 82.2, further supporting this factor beings an anthropogenic vehicle abrasion source. The third factor had a high factor loading for Iron (Fe) and a moderate factor loading for K. The median enrichment factor for K was low (2.36), and Fe is commonly associated with dust. Lastly, the fourth factor has a high factor loading for zinc

(Zn), a highly enriched element with a median CEF of 43.4. Zinc, like copper, can be used as a tracer for vehicle brake wear. However, separating a zinc factor from the copper factor indicates that the Zn in this study likely originated from motor lubricating oils.

5.4.5. Source Analysis – Volatile Organic Compounds

Table 5.13 shows the VOC compounds' loading scores above 0.30 in five principal components. Automobile sources and household products characterized the VOCs in the first component. The first four chemicals with the highest factor loadings in the first component are mainly from automobile sources, while other chemicals can be found in household products. Moreover, the components two, three, four, and five were from different household products- cleaning wipes and paint removal; soaps and detergents; toilet cleaners, bleach, and spray deodorants; and spray cleaners and fingernail polish, respectively. These classifications were based on the survey result examining commonly used household products in DHA homes. The result indicates that apart from occupant's contribution as a result of household products, outdoor sources contribute immensely to the VOC compounds detected in DHA homes. This pattern aligns with the result from source analysis for the particle-phase pollutants that indicates vehicle abrasion and lubricating oil are significant contributing sources to the indoor pollutants in DHA homes.

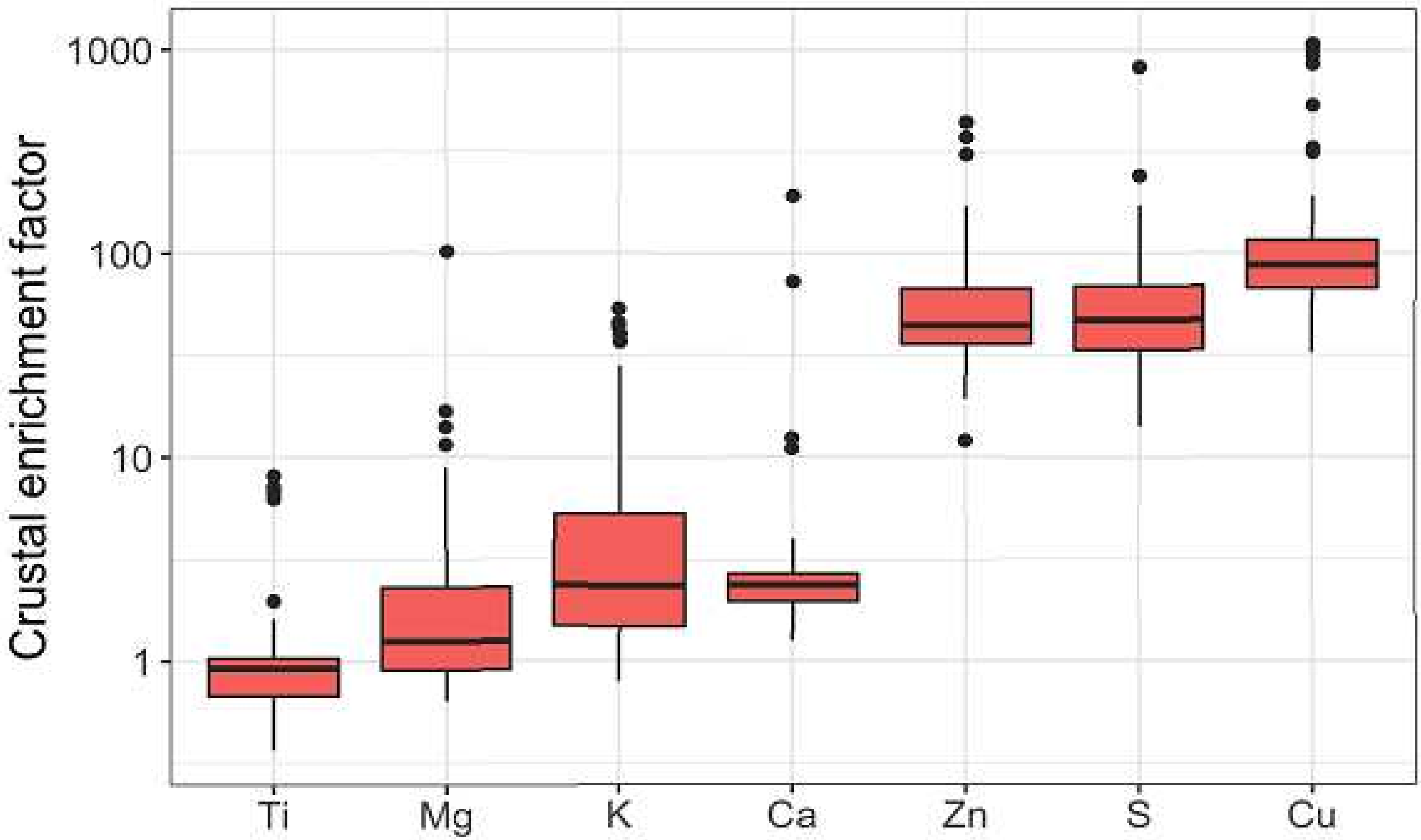

Figure 5.11: The factor loadings of the elements using the principal component analysis

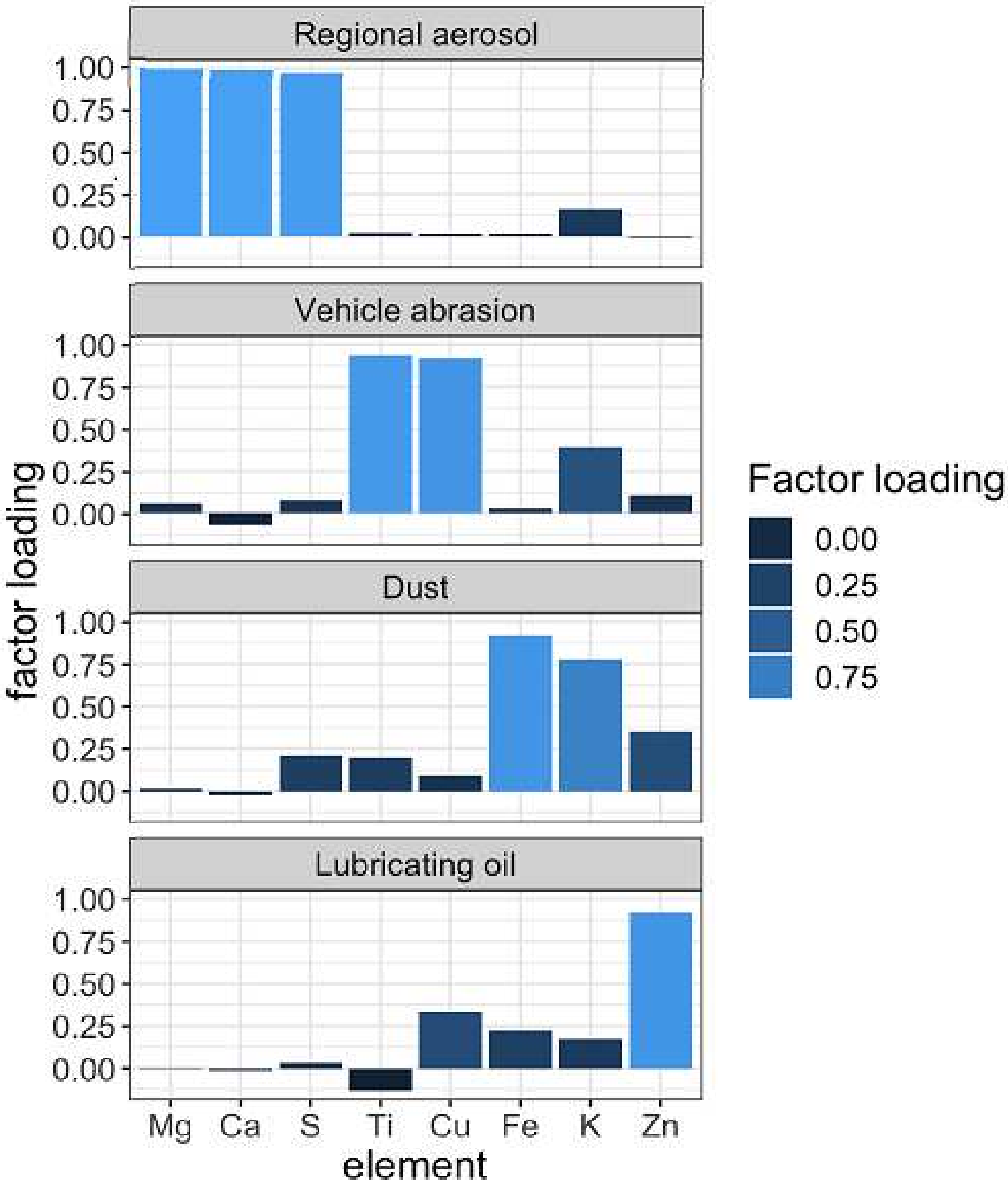

Figure 5.12: Factor loadings for the principal component analysis of $PM_{2.5}$ samples in DHA homes. Components were named post-analysis based on similar factor loadings for elemental compositions of regional aerosol, vehicle abrasion, dust, and lubricating oil.

Figure 5.13 showed the five principal components' representative (median) concentrations between DHA homes' occupied and unoccupied housing units. Components three (i.e., soaps and detergents) and four (toilet cleaners, bleach, and spray deodorants) have higher concentrations in occupied homes than unoccupied. These products are higher in occupied homes because some of the products (e.g., toilet cleaners, bleach, and spray air fresheners) have the highest usage percentage by living residents in occupied homes.

In contrast, components one (automobile and household products), two (cleaning wipes and paint removals), and five (spray cleaners and fingernail polish) are higher in unoccupied homes. Another reason why these cleaning products (e.g., cleaning wipes, spray cleaners) could be higher in unoccupied homes is that we sampled in these unoccupied residences immediately after the residents recently cleaned and vacated the units.

5.4.6. Discussion of results

One of the objectives of this study was to identify the sources of pollutants and their relative contributions to indoor air quality in DHA homes. Our approach allowed us to make some progress toward distinguishing among multiple contributing sources to indoor air quality, including occupant activity, building, and outdoor sources. For example, for the particle-phase pollutants, questionnaire data indicated that sweeping and dusting, which are daily and weekly activities of the occupants and sources of indoor PM, contributed to indoor PM more than the contributions made by PM of outdoor origin. In addition, our analysis identified targeted VOC chemicals for which occupants were the dominant source of the contribution.

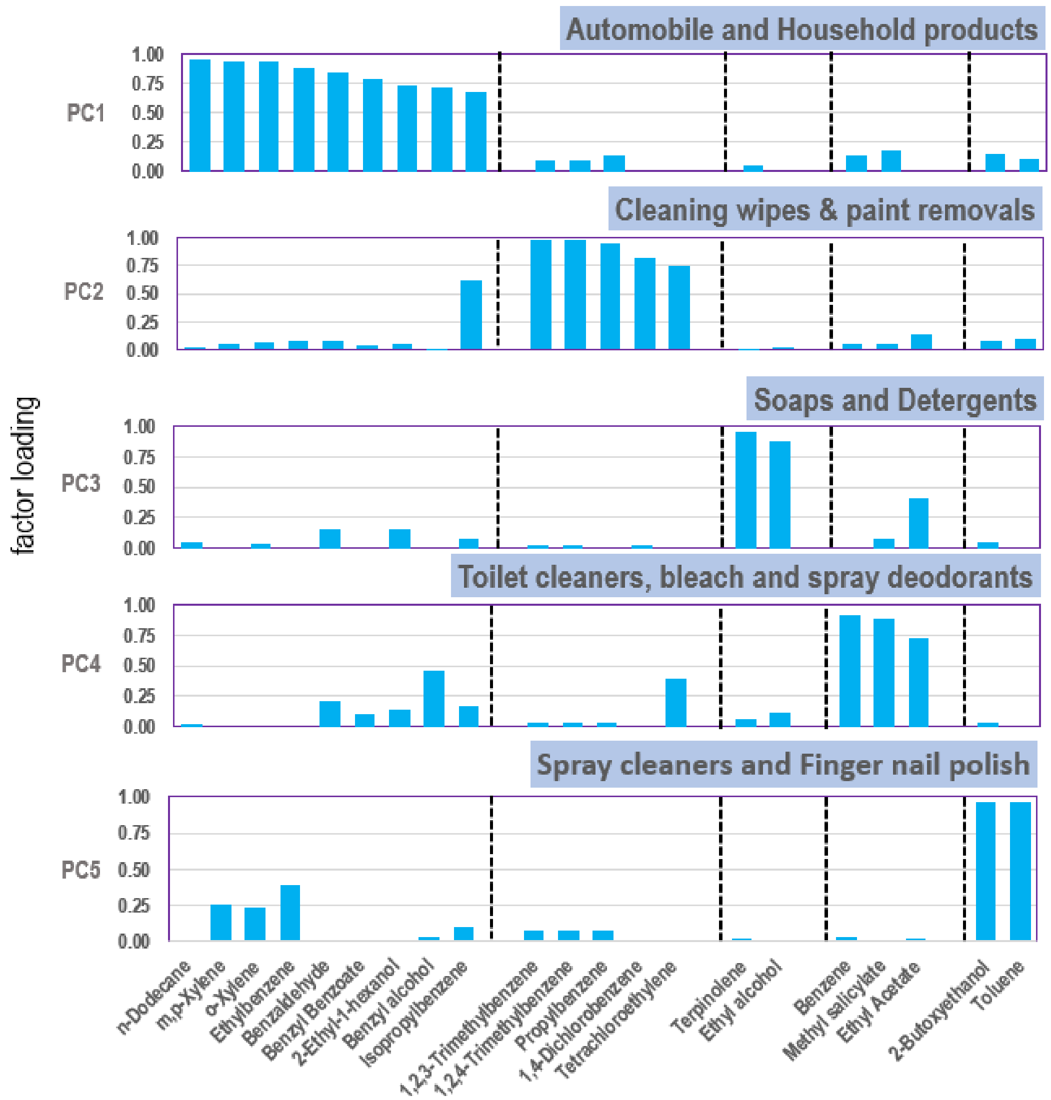

Figure 5.13: Principal component analysis showing the possible sources of VOC compounds in DHA homes

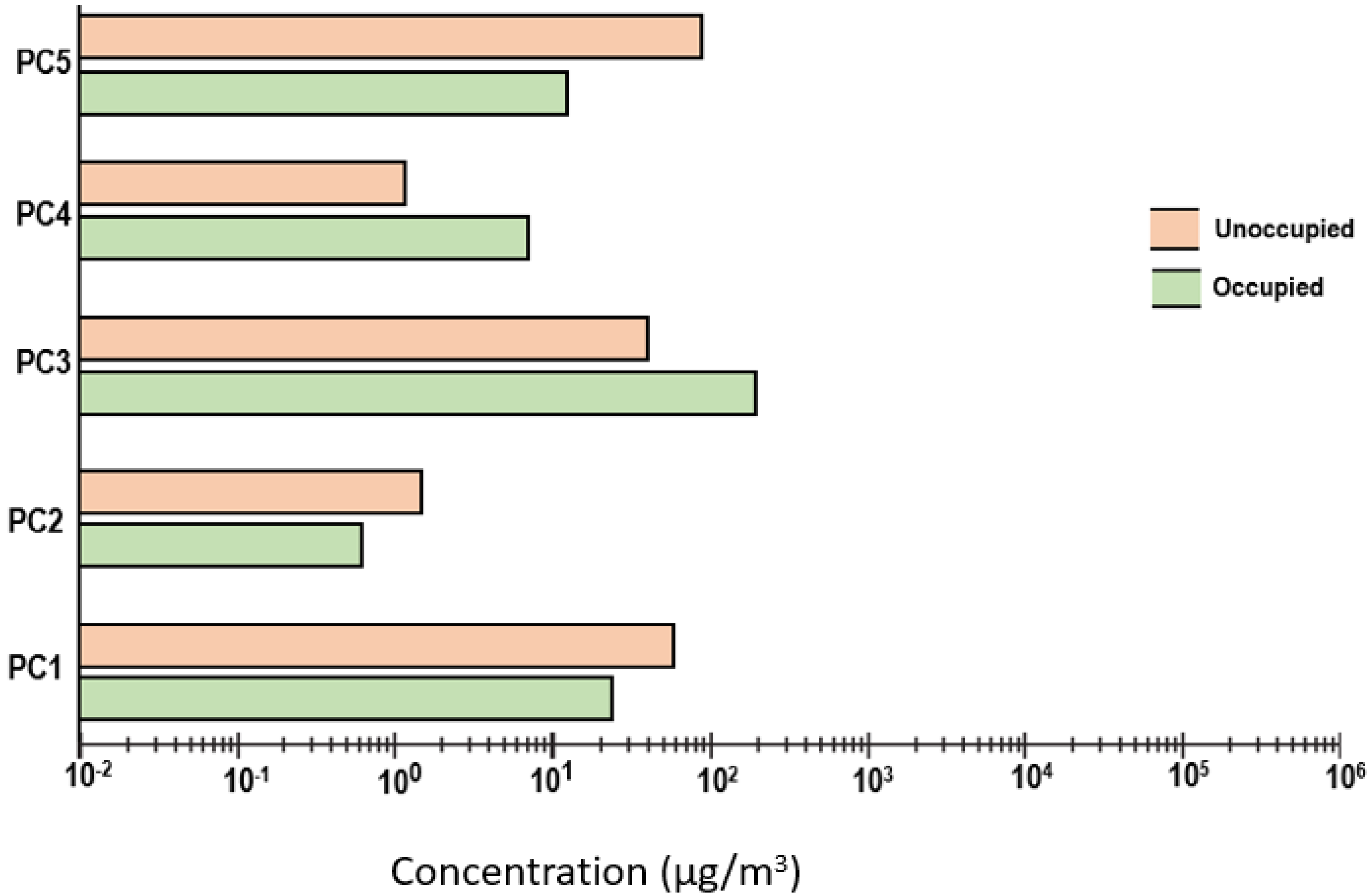

Figure 5.14: Principal component analysis showing the possible sources of VOC compounds in DHA homes

These chemicals' concentrations showed a noticeable increase in occupied housing units compared to unoccupied units. For example, the median concentration of ethyl-alcohol and ethyl acetate is significantly higher in occupied homes compared to unoccupied. Ethyl-alcohol is found in household products such as cleaning agents, detergents, fragrances, mouthwash (Dodson et al., 2017), pest-control products, and ethyl acetate is also found in nail products and paints (Goldsmith et al., 2014). The result aligns with the outcome of the survey analysis that showed percentage usage of DHA households use products that contain these compounds daily and weekly (Figure 5.1). In addition, we interpret our results to reflect that many chemicals present in unoccupied homes with median concentration levels similar or lower in occupied homes could reflect some contributions from the building sources (e.g., formaldehyde) and outdoor sources (e.g., m,p-xylene, o-xylene, and trimethylbenezes) (Table S1).

Our analysis also demonstrated the pronounced influence of outdoor sources (e.g., automobile sources or traffic) on indoor air quality in DHA homes. The DHA housing complexes in this study are situated near the highway, and there are many mechanic workshops with heavy trucks and trailers in the Sun Valley and Quigg Newton neighborhoods. Therefore, our source analysis of VOC and PM composition yielded complementary results. For instance, the source analysis of PM in DHA homes revealed contributions to indoor PM from vehicle abrasion and lubricating oil, which would both be from ambient air infiltrating indoors. In addition, the indoor to outdoor (I/O) ratio of black carbon indicated that outdoor pollutants (mainly from traffic) significantly infiltrate into both occupied and unoccupied units in DHA homes.

Prior studies have identified and reported nine (9) compounds as priority hazards in US housing stock (Logue et al., 2011). Seven of these compounds (formaldehyde, acetaldehyde, benzene, 1,4-dichlorobenzene, naphthalene, nitrogen dioxide, and $PM_{2.5}$) were found in DHA homes. These seven compounds exceed at least one national or international health standard for chronic or acute health hazards. Although not all the households have significant concentrations above the health standards, identifying the homes with a median concentration above the standards as promising candidates for exposure intervention might be a good step in the right direction towards reducing indoor environmental exposures in public housing.

This study has several limitations: first, the number of household measurements limited our ability to perform cluster analysis that could be used to identify source appointments for the chemical pollutants characterized in this study. Second, given that some of the VOC chemicals- ethanol, acetone, ethyl acetate are incredibly volatile, we did not account for their volatility in this study. Accounting for volatility would require modeling changes in source rates in occupied and unoccupied homes. In addition, we did not account for the influence of the air exchange rate (AER), which could influence the chemical concentrations, varied by occupancy in homes. This study serves as phase one, the baseline condition in DHA public homes, slated for redevelopment. Future measurements and analyses will consider the air exchange rates in newly-developed occupied homes. However, this study highlights the importance of evaluating the indoor environmental quality in public housing. Furthermore, it could help understand where to channel the resources and appropriate interventions for the multi-level interventions in household and building levels to reduce indoor pollutants.

5.5. Conclusion

This study identified the sources and their relative contributions to indoor air quality in public housing units operated by the Denver Housing Authority. Our finding showed that despite understanding how occupants' behavior could drive the indoor air quality in public housing units, outdoor sources contribute significantly to the IEQ in DHA homes more than we envisaged. Thus, outdoor sources and regional $PM_{2.5}$ emissions may be challenging to address at the household level. However, modifying source activities and building conditions (e.g., tighter building envelope and improved mechanical ventilation system) could help reduce the particle and gas-phase pollutants infiltrating indoors and may contribute to reducing exposure disparities in DHA homes.

The second phase of this study will perform similar IAQ measurements in the newly developed DHA home to support longitudinal analyses of housing redevelopment impacts on occupant health and well-being. The study will allow us to determine the differences in the IAQ between the occupant-based and non-occupant-based sources of indoor air pollution in public housing units. In addition, it will broaden our understanding of the effectiveness of sealed and tightened buildings towards reducing the outdoor pollutants in public homes.

5.6. References

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CHAPTER SIX

6.1. Conclusion

This dissertation holistically investigated three specific residential-based exposure in the United States: flooding, lead, and indoor chemical mixtures using empirically-based and modeling approaches to evaluate sources and determinants of exposure and how different population subgroups are affected. Taken together, these studies contribute to the body of literature that documents how socioeconomically disadvantaged populations tend to have higher environmental exposures, regardless of exposure type, including natural hazards (i.e., floods), legacy pollution (i.e., lead), and pollutants driven by daily human activity (whether indoor air pollutants or from outdoor origin).

One common theme that emerged from the three residential-based exposures was that the sources of environmental exposures varied within the same study and, at times, were more subtle than initially hypothesized in the literature, suggesting that more holistic approaches to exposure assessment, as were undertaken in this work, have practical value. For example, studies that have looked at exposure to environmental hazards through an environmental justice lens have reported that socioeconomically disadvantaged groups are significantly affected during flood events. However, the result in chapter 3 of this dissertation shows local deviations from the general trends and patterns indicating how socioeconomically disadvantaged and advantaged populations are affected differently during different flood types, depending on their location or region in the U.S. As another example, in the study of residential determinants of pediatric lead poisoning in Milwaukee County (chapter 4), lower blood lead levels were associated with replacement of lead pipe water service lines (i.e., premise plumbing) with copper pipes, even among children who were also likely exposed to lead through more than one pathway, including lead paint in their older homes. This result underscores the value of multi-pathway exposure assessment and interventions.

Residential interventions for in-home exposures have typically focused on a single pollutant or source of pollutants. As a result of this mindset towards residential interventions, addressing more than a single exposure often entails patching together interventions in a piecemeal and fragmented fashion. For example, residents living in flood zones could use green infrastructures such as replanting vegetation in headwaters and riparian zones, which reduce flash floods but not slow-rise floods. In addition, residents living in homes with multiple sources of lead exposure could re-paint their homes with unleaded paints or even plant grass seed, mulch, or wood chip on areas of bare soil to prevent soil lead exposure but not replace lead-pipe service lines. To prevent or limit exposure to indoor VOCs, residents could stop using VOC-emitting household products. However, they might not be able to prevent VOC emissions from outdoor sources.

The disruption to people's lives and the costs associated with residential interventions of any kind, much less those intended to address adverse environmental exposures, present high barriers to improving the quality and health of existing homes. Holistic in-home exposure assessment, as implemented in different ways throughout this dissertation, could reveal opportunities to leverage a single disruption for multiple reductions in in-home exposures. For example, complementing the green and "gray" (e.g., building levees and dredging rivers) infrastructure in some areas prone to flash and slow-rise floods or according to their effectiveness to the flood type could provide environmental and economic benefits to the residents and their properties. In addition, for lead exposure, the local government (e.g., the City of Milwaukee) and the federal government (e.g., build back better (BBB) bill) plan of replacing lead-coated pipe water service lines with copper in cities across the U.S. could significantly reduce childhood lead poisoning across the country, which was recently highlighted as a persistent, prevalent problem in this recent national-scale analysis of Americans alive today (170 million) with lead poisoning above 5 µg/dL in their early childhood (McFarland et al., 2022). Alongside local policies and actions and broad-based federal initiatives (as mentioned above), the US EPA's Lead Renovation, Repair, and Painting Rule (RRP) effort require the renovation, repair, and painting projects with lead-based paints in homes, child care facilities, and pre-schools built before 1978, is another source intervention. Coordinating the implementation of these interventions could provide a more holistic intervention to reducing childhood lead poisoning in the United States.

Exposures to indoor chemical mixtures and air pollutants, as discussed in chapter 5, present another relevant case study. Exposures to diverse chemical pollutants have been associated with adverse health issues for residents in low-income public housing units. Despite our understanding of how occupants' behavior could drive the indoor air quality in public housing units, outdoor sources contribute significantly to the indoor environmental quality in Denver Housing Authority homes more than we envisaged. Comprehensive redevelopment of the public housing stock – as is underway and planned for multiple properties in the DHA portfolio – could address multiple indoor and outdoor sources at once. For example, tighter building envelope construction and improved mechanical ventilation system in DHA homes could help reduce infiltration of outdoor particle and gas-phase pollutants at the same time that these air handling system upgrades could improve the quality of indoor air as it recirculates and exchanges with outdoor air. Evaluation of a diverse set of environmental and social impacts of DHA housing redevelopment initiatives is ongoing and planned for future community-engaged and research-driven efforts.

At the same time, not every home needs to, or should, address *all* possible in-home exposures. Holistic in-home exposure assessments can also provide the evidence needed for a resident or property manager to rank and prioritize investment, recognizing that it is as important to know what does *not* need to be addressed presently versus what does. To reduce adverse exposures and provide more measurable benefits to residents, there are also cases when it is important to customize in-home interventions to individual occupant's needs. The work presented in this dissertation adds to a substantial body of evidence that building-related exposures are diverse, unique, and may change over time. In addition, the study in Denver public housing also demonstrated the influential role in-home behaviors could play in shaping chemical exposures. For example, toilet cleaners, bleach, and spray air fresheners were the most widely used products, with reported usage in 35%, 34%, and 29% of homes, respectively. These products contain significant concentrations of the VOCs detected and measured inside DHA homes. Therefore, there is a need for in-home interventions for some types of environmental exposures that are targeted, tailored, specific, and as unique as the homes and households in which they are intended to be implemented. Pragmatic designs and stream-lined implementation of specific interventions could be more cost-effective, efficient, and ultimately support higher residential satisfaction.

Finally, the design and delivery of the home-based interventions for adverse environmental exposures through direct engagement with local decision-makers and more traditional scholarly communication channels could help uncover residents' specific challenges. In this dissertation, we worked with DHA local authorities and residents for in-home measurements and answered surveys about their homes' condition and satisfaction levels. This approach could help the DHA and HUD staff channel their resources and appropriate interventions for the multi-level interventions during the construction of the new complexes and the maintenance and management of the existing buildings.

SUPPLEMENTARY MATERIAL A1

Table S1: The representative median and upper-bound concentrations of the VOC chemicals measured in occupied and unoccupied DHA homes.

VOC compounds	Median (Occupied)	95th percentile (Occupied)	Median (Unoccupied)	95th Percentile (Unoccupied)	Med (Occupied - Unoccupied)	95th (Occupied - Unoccupied)
(S)-(+)-Carvone	0.23	1.06	0.14	0.19	0.09	0.87
1,2,3-Trimethylbenzene	0.21	0.51	0.15	0.60	0.06	-0.09
1,2,4-Trimethylbenzene	0.21	0.51	0.15	0.60	0.06	-0.09
1,3,5-Trimethylbenzene	0.06	0.29	0.38	0.75	-0.32	-0.46
1,4-Dichlorobenzene	0.12	14.47	0.92	2.13	-0.80	12.34
2,5-Dimethylfuran	0.00	0.18	0.00	0.00	0.00	0.18
2-Buthoxyethanol	13.04	490.71	89.27	3113.81	-76.24	-2623.10
2-Ethyl-1-hexanol	17.34	37.48	26.25	67.75	-8.92	-30.27
4-Allylanisole	0.00	0.07	0.00	0.00	0.00	0.07
alpha-Hexylcinnamaldehyde	0.06	0.47	0.10	0.36	-0.04	0.10
alpha-Isomethylionone	0.08	0.90	0.08	0.28	0.01	0.62
alpha-Pinene	0.69	1.81	0.35	2.25	0.34	-0.44
alpha-Terpinene	0.13	4.88	0.14	0.22	0.00	4.66
Amyl salicylate	0.03	0.28	0.03	0.17	0.00	0.11
Anethole	0.00	0.24	0.00	0.00	0.00	0.24
Benzaldehyde	7.06	18.80	9.75	41.47	-2.69	-22.67
Benzene	0.75	3.06	0.77	1.63	-0.03	1.43
Benzyl alcohol	1.23	5.61	2.47	18.72	-1.24	-13.11
Benzyl Benzoate	0.17	0.54	0.11	1.82	0.06	-1.28
beta-Caryophyllene	0.00	0.31	0.00	0.00	0.00	0.31
Camphor	0.35	2.67	0.26	1.92	0.09	0.75

VOC compounds	Median (Occupied)	95th percentile (Occupied)	Median (Unoccupied)	95th Percentile (Unoccupied)	Med (Occupied - Unoccupied)	95th (Occupied - Unoccupied)
Carbontetrachloride	0.36	0.72	0.33	0.61	0.03	0.11
Chloroform	0.72	5.80	0.83	4.00	-0.11	1.80
Coumarin	0.08	0.47	0.00	0.25	0.08	0.22
Dimethylbenzylcarbinyl acetate (DMBCA)	0.12	1.38	0.05	0.47	0.07	0.91
d-Limonene	9.25	40.85	8.62	21.32	0.62	19.52
Ethyl Acetate	3.63	19.14	0.66	2.25	2.97	16.88
Ethyl alcohol	109.60	1324.16	30.06	111.79	79.54	1212.36
Ethylbenzene	0.25	0.80	0.27	6.18	-0.03	-5.38
Galaxolide(1+2)	0.11	0.48	0.11	0.38	0.01	0.09
Geraniol	0.00	0.95	0.00	0.25	0.00	0.70
Isopropyl alcohol	160.85	608.26	228.50	634.28	-67.65	-26.03
Isopropylbenzene	0.02	0.06	0.04	0.13	-0.02	-0.07
Linalool	1.17	23.63	0.79	5.00	0.38	18.62
m,p-Xylene	0.83	2.76	0.90	32.18	-0.07	-29.42
Menthol	0.86	6.07	0.67	4.27	0.19	1.80
Methyl salicylate	0.32	3.65	0.32	1.68	0.00	1.97
Naphthalene	0.09	0.31	0.11	0.32	-0.02	-0.01
n-Decane	0.67	2.87	0.79	2.41	-0.11	0.46
n-Dodecane	0.47	1.96	0.49	11.69	-0.02	-9.73
n-Nonane	0.39	2.12	0.42	4.87	-0.03	-2.76
n-Octane	2.90	5.69	2.72	9.41	0.18	-3.72
n-Pentadecane	0.71	2.67	1.03	7.06	-0.32	-4.39
n-Tetradecane	0.91	2.66	0.74	21.67	0.17	-19.01
n-Tridecane	1.32	10.91	1.33	35.36	-0.01	-24.45
n-Undecane	0.42	5.15	2.05	6.69	-1.63	-1.54

VOC compounds	Median (Occupied)	95th percentile (Occupied)	Median (Unoccupied)	95th Percentile (Unoccupied)	Med (Occupied - Unoccupied)	95th (Occupied - Unoccupied)
o-Xylene	0.30	0.96	0.31	10.08	-0.02	-9.12
p-Isopropyltoluene	0.40	1.94	0.20	2.05	0.19	-0.11
Propylbenzene	0.05	0.12	0.06	0.16	-0.01	-0.04
Styrene	0.22	0.78	0.10	0.70	0.11	0.08
Terpineol	0.42	2.78	0.50	3.32	-0.09	-0.55
Terpinolene	0.45	8.58	0.46	3.97	-0.01	4.61
Tetrachloroethylene	0.13	1.27	0.11	0.15	0.02	1.12
Toluene	1.72	5.69	2.73	64.17	-1.00	-58.48
trans-Cinnamaldehyde	0.07	0.59	0.00	0.35	0.07	0.24
Formaldehyde	14.32	40.00	26.95	9.62	-12.63	30.38
Acetaldehyde	4.52	12.70	37.56	12.50	-33.04	0.20

Table S2: Health Standards and guidelines for criteria pollutants (µg/m3)

	Cal EPA	World Health Organization				USEPA National Air Quality Standards			
	acute (1hr)	Annual	24hr	8hr	1hr	annual	24hr	8hr	1hr
$PM_{2.5}$		10	25			15	35		
NO_2	470	40			200	100			189
CO	23000							10000	40000

Table S3: Health standards and guidelines for selected VOCs (µg/m3)

	California EPA				OSHA	USEPA	
	Acute (1hr)	8hr	Non-cancer	Cancer	8hr	Non_Cancer	Cancer
1,4-Dichlorobenzene			800	0.91	45000	800	
Benzene	1300		60	0.34		30.00	
Chloroform	150		300	1.89		98.00	1.89
Ethyl Acetate					1.40E+06		
Ethyl alcohol					1.90E+06		
Ethylbenzene			2000	4.00	435000.00	1000.00	
Isopropylbenzene					245000	400	
Naphthalene			9	0.29	50000.00	3.00	
Styrene	21000		900			900	
Tetrachloroethylene	20000		35	1.69		35.00	
Toluene	37000		300			300	
Formaldehyde	55	9.00	9	1.67		3.00	1.67
Acetaldehyde	470	300	140	4	360000	9	

In-Home Conditions & Behaviors

Start of Block: Respondent Context

Q1 Housing development

- ○ Sun Valley (1)
- ○ Westridge (2)
- ○ Quigg Newton (3)

Q2 Enumerator ID

____

Q3 Type of Interview

- ○ in-person at home (1)
- ○ in-person at community office (2)
- ○ over the phone (3)
- ○ self-administered (4)

Q4 Dwelling ID:

- ○ Layout 1 (1)
- ○ Layout 2 (2)
- ○ Layout 3 (3)

Q5 Level of Dwelling

- ○ Ground Level (1)
- ○ Second level (2)
- ○ Third level (3)

Q6 How many people live in this house at this time?

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Q167 Notes on Respondent Context

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End of Block: Respondent Context

Start of Block: Household Roster

Q7 Respondent name:

____

Q8 Respondent age:

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Q8 Respondent Gender:

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Q9 How many other adults over 18 live in this home?

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Q10 How many children under 5 live in this home?

____

Q11 How many children between the ages of 6-18 live in this home?

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Q168 Notes on Household roster

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End of Block: Household Roster

Start of Block: Housing Systems - Cooking

X→

Q12 What kind of stove do you use to cook most often?

- ○ Gas (1)
- ○ Electric (2)
- ○ Other (88) ____

Q13 Of the following, what cooking appliances do you use? [Please, check all that apply]

- ☐ Oven (1)
- ☐ Stove/Range (2)
- ☐ Microwave (3)
- ☐ Toaster (4)
- ☐ Toaster Oven (5)
- ☐ Hot Plate (6)
- ☐ Outdoor Grill (7)
- ☐ Indoor Grill (8)
- ☐ Rice cooker (9)
- ☐ Slow cooker (10)
- ☐ Pressure cooker (11)
- ☐ Other (12)

Q183 At this time of year, how often do YOU use each appliance?

	Daily (1)	Weekly (2)	A few times a month (3)	Never (4)
Oven (Q183_1)	o	o	o	o
Stove/Range (Q183_2)	o	o	o	o
Microwave (Q183_3)	o	o	o	o
Toaster (Q183_4)	o	o	o	o
Toaster Oven (Q183_5)	o	o	o	o
Hot Plate (Q183_6)	o	o	o	o
Outdoor Grill (Q183_7)	o	o	o	o
Indoor Grill (Q183_8)	o	o	o	o
Rice Cooker (Q183_9)	o	o	o	o
Slow Cooker (Q183_10)	o	o	o	o
Pressure Cooker (Q183_11)	o	o	o	o
Other (Q183_88)	o	o	o	o

Q184 At this time of year, how often do other adults in the household use each appliance?

	Daily (1)	Weekly (2)	A few times a month (3)	Never (4)
Oven (Q184_1)	○	○	○	○
Stove/Range (Q184_2)	○	○	○	○
Microwave (Q184_3)	○	○	○	○
Toaster (Q184_4)	○	○	○	○
Toaster Oven (Q184_5)	○	○	○	○
Hot Plate (Q184_6)	○	○	○	○
Outdoor Grill (Q184_7)	○	○	○	○
Indoor Grill (Q184_8)	○	○	○	○
Rice Cooker (Q184_9)	○	○	○	○
Slow Cooker (Q184_10)	○	○	○	○
Pressure Cooker (Q184_11)	○	○	○	○
Other (Q184_88)	○	○	○	○

Q169 Notes on Cooking

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End of Block: Housing Systems - Cooking

Start of Block: Housing Systems - Cleaning

X→

Q16 Is there a doormat outside the front entrance?

◯ Yes (1)

◯ No (0)

X→

Q17 Is there a doormat inside the front entrance?

◯ Yes (1)

◯ No (0)

Q18 At this time of year, how often do you do the following activities?

	Daily (1)	Weekly (2)	A few days per month (3)	Never (4)
Sweep (1)	○	○	○	○
Vacuum (2)	○	○	○	○
Dust (3)	○	○	○	○
Mop (4)	○	○	○	○

Q19 At this time of year, how often do other adults in your household do the following activities?

	Daily (1)	Weekly (2)	A few days per month (3)	Never (4)
Sweep (1)	○	○	○	○
Vacuum (2)	○	○	○	○
Dust (3)	○	○	○	○
Mop (4)	○	○	○	○

Q170 Notes on Cleaning

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End of Block: Housing Systems - Cleaning

Start of Block: Heating and Cooling

Q20 Do you have a thermostat in your home?
[A thermostat tells you the temperature of your home and lets you change the temperature]

- Yes (1)
- No (0)
- Don't know (99)

Q21 If yes, what is the current temperature shown on the thermostat?

____

Q22 If known, what is the humidity level in the room?

- ○ very dry (4)
- ○ dry (5)
- ○ humid (6)
- ○ very humid (7)

Q149 Notes for humidity question (Q22)

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Q23 During the summer and warmer months, what do you do when it's too hot inside your home?

- ☐ Shed some clothing (1)
- ☐ Close/open blinds/shades (2)
- ☐ Open windows (3)
- ☐ Open doors (9)
- ☐ Turn on air-conditioner (4)
- ☐ Turn on portable/standing fan (5)
- ☐ Turn on ceiling fan (6)
- ☐ Turn down the thermostat (7)
- ☐ Other (8) ____

Q24 During the winter and colder months, what do you do when it’s too cold inside your home?

- ▢ Close/open blinds/shades (1)
- ▢ Turn up the thermostat (2)
- ▢ Use a portable heater (3)
- ▢ Wear extra clothing (4)
- ▢ Use extra blanket or a warmer blanket at night (5)
- ▢ Turn on the oven (6)
- ▢ Other (7)

Q25 Right now, the indoor temperature feels:

- ○ Very hot (1)
- ○ Hot (2)
- ○ Slightly hot (3)
- ○ Moderate (4)
- ○ Slightly cold (5)
- ○ Cold (6)
- ○ Very cold (7)

Q26 Right now, the indoor moisture feels:

- Very humid (1)
- Moist (2)
- Slightly Moist (3)
- Moderate (4)
- Slightly dry (5)
- Dry (6)
- Very dry (7)

Q27 Right now, the indoor wind speed feels:

- No wind (1)
- Breeze (2)
- Small wind speed (3)
- Moderate (4)
- Wind speed is slightly large (5)
- Wind speed is large (6)
- Wind speed is very high (7)

Q28 Right now, how comfortable are you with the temperature of your home?

- Very satisfied (1)
- Satisfied (2)
- Dissatisfied (3)
- Very dissatisfied (4)

Q29 In general, when you are trying to stay cool, how satisfied are you with the temperature of your home?

- Very satisfied (1)
- Satisfied (2)
- Dissatisfied (3)
- Very dissatisfied (4)

Q30 In general, when you are trying to stay warm, how satisfied are you with the temperature of your home?

◯ Very satisfied (1)

◯ Satisfied (2)

◯ Dissatisfied (3)

◯ Very dissatisfied (4)

Q171 Notes on Heating and Cooling

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End of Block: Heating and Cooling

Start of Block: Ventilating - Kitchen

Q31 Is there an exhaust fan near your stove in the kitchen?
[Please, refer to the pictures]

◯ Yes (1)

◯ No (0)

Q32 Does the fan work?
[Refer to the picture booklet on how to test the fan]

- ○ Yes (1)
- ○ No (0)

Q33 What form of ventilation is above or next to the main cooking appliance or area in the kitchen?

- ○ Exhaust fan - Recirculation (1)
- ○ Exhaust fan - to the outdoors (2)
- ○ Fan in the wall (3)
- ○ Passive trickle vent to outside (4)
- ○ Windows (5)
- ○ Other (6) ____
- ○ No ventilation (7)

Q34 How often do you turn the fan on? *[select all that apply]*

○ Whenever I'm cooking (1)

○ Occasionally (2)

○ Rarely (3)

○ Never (4)

Q35 How often do other adults turn the fan on? *[select all that apply]*

○ Whenever they are cooking (1)

○ Ocassionally (2)

○ Rarely (3)

○ Never (4)

Q172 Notes on Kitchen ventilation

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End of Block: Ventilating - Kitchen

Start of Block: Ventilating - Bathroom

Q151 How many bathrooms are in this residence?

- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)

Q36 What form of ventilation is in each bathroom?

	Exhaust fan (1)	Vents (2)	Windows (3)	No ventilation (4)
Bathroom 1 (1)	▢	▢	▢	▢
Bathroom 2 (2)	▢	▢	▢	▢
Bathroom 3 (3)	▢	▢	▢	▢

Q37 How is bathroom ventilation controlled?

	With light (1)	Separate control (2)	Other (88)	No fan (0)
Bathroom 1 (1)	☐	☐	☐	☐
Bathroom 2 (2)	☐	☐	☐	☐
Bathroom 3 (3)	☐	☐	☐	☐

Q38 Does it work?

	Yes (1)	No (0)
Bathroom 1 (1)	○	○
Bathroom 2 (2)	○	○
Bathroom 3 (3)	○	○

Q39 Is the fan suction adequate? (hold toilet paper to entire fan face to test suction)

- ○ Yes (1)
- ○ No (0)
- ○ Couldn't conduct test (99)

Q40 How often do YOU use the bathroom fan?

- ○ Whenever I'm using the bathroom (1)
- ○ Occasionally (2)
- ○ Rarely (3)
- ○ Never (4)

Q41 How often do other adults use the bathroom fan?

- ○ Whenever they are using the bathroom (1)
- ○ Ocassionally (2)
- ○ Rarely (3)
- ○ Never (4)

Q173 Notes on Bathroom ventilation

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End of Block: Ventilating - Bathroom

Start of Block: Lighting

Q42 Number of light fixtures:

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Q43 Number of lamps/lights:

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Q174 Notes on lighting

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End of Block: Lighting

Start of Block: Waste and Pest Management

Q152 How do you dispose of garbage in your kitchen?

- ☐ garbage can (1)
- ☐ disposable bag (2)
- ☐ no garbage can or bag (3)

Q153 Where do you place the bags

- ○ Indoors (1)
- ○ Outdoors (3)

Q154 Notes on bag placement

____

Q44 If garbage is stored in the kitchen, is the container covered with a lid?

- ○ Yes (1)
- ○ No (0)

Q45 If garbage is stored elsewhere in the home, is the container covered with a lid?

- Yes (1)
- No (0)

Q46 In the kitchen, are there any open food sources?

- Yes (1)
- No (2)

Q47 Have you (or other members of your household) observed live pests in your residence?

- Yes (1)
- No (2)

Q48 Which pests have you or members of your household observed?

- ☐ Cockroaches (1)
- ☐ Ants (2)
- ☐ Mice (3)
- ☐ Rats (4)
- ☐ Other (88) ____

X→

Q49 Have you or other members of your household ever used any of the following pest control devices?

- ☐ Foggers or Bombs (1)
- ☐ Gels (2)
- ☐ Powder pesticides (3)
- ☐ Spray pesticides (4)
- ☐ Moth balls (5)
- ☐ Other (88) ____

Q50 How often do you (or other members of your household) use the pest control devices?

- Daily (1)
- A few times a week (2)
- A few times a month (3)
- A few times a year (4)
- Never (5)

X→

Q51 In the last 12 months, how frequently have you or someone in your residence used pest control devices?

- Daily (1)
- A few times a week (2)
- A few times a month (3)
- A few times a year (4)
- Never (5)

Q175 Notes on Pest Management

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End of Block: Waste and Pest Management

Start of Block: Water-and Mold-Related Issues

Q52 Are there any water leaks evident in the kitchen?

- Yes (1)
- No (0)

53 Are pipe penetrations sealed in the kitchen (refer to pictures)?

- Yes (1)
- No (0)

54 Are there any water leaks evident in the bathroom(s)?

- Yes (1)
- No (0)

55 Are pipe penetrations sealed in the bathroom(s) (refer to pictures)?

- Yes (1)
- No (0)

---

56 Any visible sign of mold in any room in your home?

- Yes (1)
- No (0)

---

57 Are there any water leaks evident elsewhere in the home?

- Yes (1)
- No (0)

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58 Do you currently have mold in your residence?

- Yes (1)
- No (3)

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59 Have you seen any mold on any surfaces (i.e. walls, ceilings, floor) in your residence in the last 12 months?

- Yes (1)
- No (0)

60 In what rooms have you seen mold?

- 1 bathroom (1)
- More than 1 bathroom (2)
- Living room (3)
- 1 bedroom (4)
- More than 1 bedroom (5)
- Kitchen (6)
- Other (88) ____

61 In a typical day, what is the total number of showers or baths taken in your residence?

- Less than 1 (1)
- One (2)
- Two (3)
- Three (4)
- Four (5)
- More than 4 (6)

Q176 Notes on Water & Mold

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End of Block: Water-and Mold-Related Issues

Start of Block: Safety

62 Is there a working smoke alarm in your residence?

- Yes (1)
- No (0)

63 Is there a working carbon monoxide alarm in your residence?

- Yes (1)
- No (0)

Q177 Notes on Safety

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End of Block: Safety

Start of Block: Sources

64 Are any of these devices or products used in the home? (Select all that apply)

- ☐ Solid air freshener (1)
- ☐ Plug-in air freshener (2)
- ☐ Spray air freshener (3)
- ☐ Humidifier (4)
- ☐ De-humidifier (5)
- ☐ Portable-heater (6)
- ☐ Air-cleaning device (7)
- ☐ Window-air conditioner (8)
- ☐ Fingernail polish (11)
- ☐ Spray deodorant (12)
- ☐ Spray-on glass cleaner (13)
- ☐ Bleach (14)
- ☐ Furniture polish (15)
- ☐ Toilet cleaner (16)
- ☐ Other (88) ____

65 How often do you use the devices or products?

	Daily (1)	A few times a week (2)	A few times a month (3)	A few times a year (4)	Never (5)
Solid air freshener (1)	○	○	○	○	○
Plug-in air freshener (3)	○	○	○	○	○
Spray air freshener (4)	○	○	○	○	○
Humidifier (5)	○	○	○	○	○
De-humidifier (6)	○	○	○	○	○
Portable-heater (7)	○	○	○	○	○
Air-cleaning device (8)	○	○	○	○	○
Window-air conditioner (9)	○	○	○	○	○
Fingernail polish (12)	○	○	○	○	○
Spray deodorant (13)	○	○	○	○	○
Spray-on glass cleaner (14)	○	○	○	○	○
Bleach (15)	○	○	○	○	○
Furniture polish (16)	○	○	○	○	○
Toilet cleaner (17)	○	○	○	○	○

Other (18)	○	○	○	○	○

66 Any sign of peeling paint in the residence?

○ Yes (1)

○ No (0)

67 How often in the last twelve months have you smelled each type of odor in the residence coming from other residences or the hallway?

	Everday (4)	A few times a year (3)	A few times a week (2)	A few times a month (1)	Never (0)
Cigarette (1)	○	○	○	○	○
E-cigarettes (2)	○	○	○	○	○
Marijuana (3)	○	○	○	○	○
Cooking odors (4)	○	○	○	○	○
Garbage (5)	○	○	○	○	○
Other: (7)	○	○	○	○	○

68 Among the members of this household, how many individuals smoke any of the above (cigarettes, e-cigarettes, and/or marijuana)?

____

69 Do you ever notice people smoking near your residence?

○ Yes (1)

○ No (0)

Q178 Notes on Sources

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End of Block: Sources

Start of Block: Resident Rating of their Dwelling

70 How long have you lived in this home?

- ○ Less than one month (1)
- ○ more than 1 month, but less than 6 months (2)
- ○ 6 months or more, but less than 12 months (3)
- ○ a year or more, but less than 2 years (4)
- ○ 2 years or more, but less than 5 years (5)
- ○ 5 years or more, but less than 10 years (6)
- ○ 10 years or more (7)

Q160 Overall, how satisfied are you with your home?

- Very dissatisfied (1)
- Generally dissatisfied (2)
- Generally satisfied (3)
- Very satisfied (4)

---

72 On a scale of 1 to 10, with 1 being the worst and 10 being the best, how would you rate your home overall right now as a place to live?

- 1 (4)
- 2 (5)
- 3 (6)
- 4 (7)
- 5 (8)
- 6 (9)
- 7 (10)
- 8 (11)
- 9 (12)
- 10 (13)

Q185 On a scale of 1 to 10, with 1 being the worst and 10 being the best, how would you rate the overall cost of housing for you right now?

- ○ 1 (4)
- ○ 2 (5)
- ○ 3 (6)
- ○ 4 (7)
- ○ 5 (8)
- ○ 6 (9)
- ○ 7 (10)
- ○ 8 (11)
- ○ 9 (12)
- ○ 10 (13)

Q186 Do you expect that you will have a place to live for the foreseeable future?

- ○ Yes (1)
- ○ No (0)
- ○ Not sure (99)

Q187 On a scale of 1 to 10 (where 1 is the least confident and 10 is the most confident) how confident do you feel that you will be able to live in Sun Valley as long as you desire?

- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)
- ○ 6 (6)
- ○ 7 (7)
- ○ 8 (8)
- ○ 9 (9)
- ○ 10 (10)

Q188 On a scale of 1 to 10, with 1 being the worst and 10 being the best, how would you rate Sun Valley as a neighborhood to live in?

- ◯ 1 (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 (7)
- ◯ 8 (8)
- ◯ 9 (9)
- ◯ 10 (10)

Q189 On a scale of 1 to 10, with 1 being the worst and 10 being the best, how would you rate the overall condition of your housing for you right now?

- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)
- ○ 6 (6)
- ○ 7 (7)
- ○ 8 (8)
- ○ 9 (9)
- ○ 10 (10)

Q190 What are two or three things you like about your home?

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Q191 What are two or three things you don’t like about your home?

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Q192 What are two or three things that you would like to change about your home?

____

____

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____

73 Overall, how satisfied are the other adults in your household with their home?

- ○ Very satisfied (1)
- ○ Generally satisfied (2)
- ○ Generally dissatisfied (3)
- ○ Very dissatisfied (4)

Q162 On a scale of (0-10) (0:worst; 10: best), how satisfied are the other adults in your household with their home?

- ○ 0 (1)
- ○ 1 (2)
- ○ 2 (3)
- ○ 3 (4)
- ○ 4 (5)
- ○ 5 (6)
- ○ 6 (7)
- ○ 7 (8)
- ○ 8 (9)
- ○ 9 (10)
- ○ 10 (11)

74 On a scale of 0-10 (0: worst; 10: best), how would the other adults in in your household rate their home right now as a place to live?

- ○ 1 (4)
- ○ 2 (5)
- ○ 3 (6)
- ○ 4 (7)
- ○ 5 (8)
- ○ 6 (9)
- ○ 7 (10)
- ○ 8 (11)
- ○ 9 (12)
- ○ 10 (13)

Q155 How often do you call maintenance when things are broken in the house?

- ○ Never (1)
- ○ Less than 1 time per month (2)
- ○ 1 or 2 times per month (3)
- ○ 3-4 times per month (4)
- ○ More than 4 times per month (5)

Q157 On a scale of 1-10; how satisfied are you with the response of the maintenance?

- ◯ 1 (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 (4)
- ◯ 5 (5)
- ◯ 6 (6)
- ◯ 7 (7)
- ◯ 8 (8)
- ◯ 9 (9)
- ◯ 10 (10)

Q158 Are you currently in the process of moving?

- ◯ yes (1)
- ◯ no (2)

Q156 Notes on Resident dwelling rating (Include notes to ask whether maintenance satisfaction is before or during moving process .)

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End of Block: Resident Rating of their Dwelling

Start of Block: Time-Activity Patterns

75 How many hours do you spend in your residence during a typical weekday (Mon-Fri)?

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77 How many hours do you spend in your residence during a typical weekend (Sat-Sun)?

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Q163 Is the amount of time spent in your home now the same or different from pre-COVID-19?

○ same (1)

○ different (2)

X→

76 Currently, during a typical weekday, how often are you at home during the following blocks of time?

	Always (1)	Sometimes (2)	Never (3)
Morning (8AM - 12PM) (76_1)	○	○	○
Afternoon (12 PM - 4 PM) (76_2)	○	○	○
Evening (4 PM - 10 PM) (76_3)	○	○	○
Night (10 PM - 8AM) (76_4)	○	○	○

X→ X→

Q110 Currently, during a typical weekday, how often are **others in your household** at home during the following blocks of time?

	Always (1)	Sometimes (2)	Never (3)
Morning (8AM - 12PM) (Q110_1)	○	○	○
Afternoon (12 PM - 4 PM) (Q110_2)	○	○	○
Evening (4 PM - 10 PM) (Q110_3)	○	○	○
Night (10 PM - 8 AM) (Q110_4)	○	○	○

Q113 Currently, during a typical weekend, how often are **you** at home during the following blocks of time?

	Always (1)	Sometimes (2)	Never (3)
Morning (8AM - 12PM) (Q110_1)	o	o	o
Afternoon (12 PM - 4 PM) (Q110_2)	o	o	o
Evening (4 PM - 10 PM) (Q110_3)	o	o	o
Night (10 PM - 8 AM) (Q110_4)	o	o	o

Q115 Currently, during a typical weekend, how often are **others in your household** at home during the following blocks of time?

	Always (1)	Sometimes (2)	Never (3)
Morning (8AM - 12PM) (Q110_1)	o	o	o
Afternoon (12 PM - 4 PM) (Q110_2)	o	o	o
Evening (4 PM - 10 PM) (Q110_3)	o	o	o
Night (10 PM - 8 AM) (Q110_4)	o	o	o

Q180 Notes on Time Activity Patterns

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End of Block: Time-Activity Patterns

Start of Block: Sleep Patterns

Q116 What time do you usually go to bed?

○ On weekdays (work or school days)? (1) ____

○ On weekends? (2) ____

Q117 What time do you usually wake up?

○ On weekdays (work or school days)? (4) ____

○ On weekends? (5) ____

Q119 How many hours does it usually take for you to fall asleep at bedtime?

- ○ less than an hour (4)
- ○ 1-2 hours (5)
- ○ more than 2 hours (6)

Q120 How many hours of wake time (waking up in the middle of the night) do you have during a typical night's sleep?

- ○ less than an hour (4)
- ○ 1-2 hours (5)
- ○ more than 2 hours (6)

Q121 During a typical week, how many times do you nap for 5 minutes or more?

- ○ None (0)
- ○ One or more (1)

Q125 Over the past 4 weeks, how often have you snored?

- Never (1)
- Rarely (1-2 nights per week) (2)
- Sometimes (3-5 nights per week) (3)
- Always (6-7 nights per week) (4)

Q126 Have you ever been told by a doctor or other health professionals that you have any of the following?

- Sleep apnea or obstructive sleep apnea *(disorder associated with snoring that is typically diagnosed after a sleep study is done and shows that your breathing stops and starts over the night)* (1)
- Insomnia *(condition, lasting one month or longer, characterized by frequent problems getting to sleep at night or staying asleep, or both)* (3)
- Restless legs *(disorder in which you have an uncontrollable urge to move your legs or arms, usually due to uncomfortable feelings - creeping, tugging or pulling - in the legs or arms, that are usually worse in the evenings and can cause you to wake at night)* (5)
- None of the above (6)

X→ X→

Q127 How much do you agree or disagree with the following statements?

	Strongly disagree (1)	Disagree (2)	Unsure (3)	Agree (4)	Strongly agree (5)	Not applicable (99)
Sometimes my sleep is affected because I feel unsafe at night (Q127_1)	○	○	○	○	○	○
The place where I sleep is physically comfortable (mattress, pillows, etc.) (Q127_2)	○	○	○	○	○	○
The place where I sleep is at a comfortable temperature (Q127_3)	○	○	○	○	○	○
My sleep is sometimes affected by my bed partner's sleep schedule or habits while in bed (reading, moving about snoring, etc.) (Q127_4)	○	○	○	○	○	○

Q128 Is the room where you sleep quiet at night?

○ Always (1)

○ Sometimes (2)

○ Never (3)

Q129 If it is noisy, what makes it noisy? (Select all that apply)

▢ Other people at home (1)

▢ Neighbors (2)

▢ Noise from the street (3)

▢ Television or Radio in the bedroom (5)

▢ Other (4) ____

X→

Q130 Is the room where you sleep dark during the night (or day if you work at night)?

○ Yes (1)

○ No (0)

Q131 Why is it not dark?

- ◯ Lights from my bedroom (5)
- ◯ Light from other rooms (1)
- ◯ Light from the street (2)
- ◯ Other: (4) ____

Q166 On a scale of 1-5, (1: worse; 5: best), how would you rate your typical night's sleep in the past 4 weeks?

- ◯ 1 (1)
- ◯ 2 (2)
- ◯ 3 (3)
- ◯ 4 (4)
- ◯ 5 (5)

Q124 Overall, how was your typical night's sleep during the past 4 weeks?

- ◯ Very sound and restful (1)
- ◯ Sound and restful (2)
- ◯ Average quality (3)
- ◯ Restless (5)
- ◯ Very restless (6)

Q181 Notes on Sleep Patterns

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End of Block: Sleep Patterns