

Costs and Benefits of Building Airtightness Improvements for Air Pollution Exposure and Human Health

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

Air pollution is the largest global environmental health threat; fine particulate matter (PM_{2.5}) alone, as the most harmful air pollutant, is associated with millions of premature deaths each year. Most studies focus on the impacts of changes in outdoor air PM_{2.5} on human health. This overlooks the fact that most exposure to PM_{2.5} of outdoor-origin occurs indoors, as people tend to spend most of their time indoors, and that the pollution infiltrates the building envelope. Specifically, Americans spend almost 70% of their time in their homes, and approximately 50% of outdoor-origin PM_{2.5} health burdens are due to residential exposure.

To better understand the effect of this infiltration on human health, and to explore opportunities for improvement, this study examines the health impact of enhancing building airtightness, particularly in single-family homes where approximately 75% of the U.S. population resides. This thesis conducts a historical study on modeled daily average PM_{2.5} levels between the years 1980 to 2010 in the United States to examine the national and spatial costs and benefits associated with improving the airtightness of these homes to mitigate the health effects of air pollution.

To achieve this, an integrated modeling framework was developed, which incorporates mass balance modeling, health impact modeling, and economic modeling. This framework was used to establish baseline and alternative levels of exposure to outdoor-origin PM_{2.5} across the historic building stock in the contiguous United States under the current state and post-intervention state. Subsequently, it evaluates the health benefits and retrofit costs associated with improving airtightness levels. The primary scenarios evaluated involve enhancing building air sealing to meet the standards mandated by the International Energy Conservation Code (IECC) 2018. Additionally, secondary scenarios of 20%, 25%, 40%, and 60% air leakage reductions were also considered.

This study analyzes the benefits of improving three distinct building age groups. The results reveal that enhancing the airtightness of single-family homes up to IECC 2018 mandates results in interventions costing approximately \$105 (\$102, \$107) billion nationally. However, they could save about 44,611 (29,831, 58,905) lives annually and deliver annual health benefits valued up to \$356 (\$45, \$1,173) billion in 2020 USD. The result is an annual net benefit of approximately \$251 (-\$62, \$1,067) billion in 2020 USD, in the intervention year. This study also indicates that older homes, particularly those constructed before 1940, exhibit the greatest reductions in indoor PM_{2.5} levels from outdoor sources. These homes demonstrate a potential annual benefit of \$55 (\$7, \$193) billion in 2020 USD and 7,104 (4,655, 9,832) lives saved, translating to about \$3,066 (\$390, \$10,759) in 2020

USD in benefits per resident annually. On a per-house basis, the cost of improvements in these older homes averages \$1,686 (\$1,616, \$1,756) in 2020 USD, while the net benefit per resident can reach up to \$2,263 (-\$442, \$9,825) in 2020 USD in the year of intervention.

Significant spatial variability in benefits exists, with the greatest impacts observed in the eastern U.S. due to higher regional pollution levels and leakier homes. Further, there is uncertainty associated with model parameters, particularly associated with the health response to exposure. Despite these uncertainties, most interventions studied show large mean net benefits.

These findings strongly support that targeted enhancement of building airtightness substantially impacts public health and should be considered by decision-makers when designing building standards or developing retrofit plans.

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Dedication

I dedicate this research to my loved ones and all who supported me in achieving this academic milestone. First and foremost, I thank my parents, without whom none of this would have been possible. Special thanks to my grandmother and aunt, who have helped me in countless ways. I am grateful to Mohammad and Lauren, who made me feel at home in Waterloo. My heartfelt gratitude goes to all my dear friends; there is not enough space here to thank each of you thoroughly.

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Chapter 1

Introduction

Many epidemiology studies have directed their efforts toward associating chronic exposure to air pollution with adverse health impacts. Among all forms of air pollution, it is well established that inhaling particulate matter (PM), particularly fine particulate matter with an aerodynamic diameter of 2.5 micrometers or less (referred to as $\text{PM}_{2.5}$), can result in various adverse health effects. These effects include respiratory infections, heart disease, and lung cancer, among others (Burnett et al., 2018; Pope et al., 2018; Sacks et al., 2011). Due to these health impacts, there are yearly close to 9 million premature deaths linked to ambient $\text{PM}_{2.5}$ exposure across the globe (Burnett et al., 2018), making it the fifth-ranking mortality risk factor worldwide (Cohen et al., 2017), and the biggest environmental threat to human health (Hoffmann et al., 2021). The premature mortality and morbidity resulting from exposure to ambient $\text{PM}_{2.5}$ are estimated to cause trillions of dollars in damages globally (World Bank, 2020). The United States is also not immune from these health impacts; in the United States alone, exposure to $\text{PM}_{2.5}$ is responsible for approximately 130,000 premature deaths each year (Fann et al., 2012).

While the literature has primarily focused on outdoor levels of $\text{PM}_{2.5}$, and numerous studies have examined the health impacts and mortality changes due to the reduction of outdoor $\text{PM}_{2.5}$ and policies that aim to mitigate the emission of such particles at their sources (Fann, Baker, & Fulcher, 2012; Wang et al., 2020), it is important to recognize that fluctuations in emission of outdoor $\text{PM}_{2.5}$ at sources is not the full story behind changes in adverse health event incidences due to exposure to outdoor-origin $\text{PM}_{2.5}$. In reality, indoor exposure to and inhalation of $\text{PM}_{2.5}$ contributes significantly to the health burdens (Bhoonah et al., 2023).

Americans typically spend the majority of their time in environments other than out-

doors, including enclosed spaces. Based on the National Human Activity Pattern Survey (NHAPS) sponsored by U.S. Environmental Protection Agency (EPA), Americans self-reported their time activity budgets as follows: 5.5% of time in vehicles, 68.7% in residential buildings, 18.2% in other types of buildings, and only 7.6% of their time outside (Klepeis et al., 2001). Studies have shown that most of the exposure to outdoor-origin $\text{PM}_{2.5}$ occurs in environments other than outdoors (Azimi & Stephens, 2020). This highlights the importance of studies that, instead of evaluating health impacts based on changes in $\text{PM}_{2.5}$ emissions at the source, focus on controlling $\text{PM}_{2.5}$ levels within indoor environments.

Among all the environments in which individuals spend their time, multiple studies have emphasized the importance of residential exposure to $\text{PM}_{2.5}$. Logue et al. (2012) associates more than 100 deaths per 100,000 people annually due to residential exposure to $\text{PM}_{2.5}$. Azimi and Stephens (2020) concluded that residential exposure accounts for approximately 67% of the deaths related to exposure to outdoor sources of $\text{PM}_{2.5}$ in the United States. Fisk (2015) estimates that roughly 65% of people’s inhalation of wildfire caused particles happen indoors. In another study, Ji and Zhao (2015) aimed to determine the proportion of indoor PM from outdoor sources to the total mortality caused by outdoor PM. They collected data on all-cause, cardiovascular, and respiratory mortalities across the United States, China, Europe, and the world and found that 81% to 89% of overall mortalities associated with outdoor PM pollution actually occur indoors due to the infiltration of pollutants into buildings.

The quality of our homes can play an important role in protecting us from air pollution. Ji and Zhao (2015) emphasized that better-designed buildings capable of protecting their residents from outdoor air pollution would significantly improve public health. Additionally, a report by Fisk (2015) also highlighted the role of building improvements in better protecting human health and discussed measures such as particle-capturing equipment or tightening buildings. As mentioned before, with climate change $\text{PM}_{2.5}$ levels are expected to get worse (Silva et al., 2017). Sparks et al. (2024) argues that, under climate change, the number of days with air quality alerts will also increase. As a form of adaptation, more people will likely move inside buildings to protect themselves from air pollution. However, the effectiveness of their adaptive behavior depends on how protective the buildings are (Sparks et al., 2024).

Despite the acknowledged importance of buildings in safeguarding human health, pollutant concentrations in many buildings exceed standards, and severe outdoor $\text{PM}_{2.5}$ can further increase indoor $\text{PM}_{2.5}$ concentrations (Liu et al., 2022). It is important to note that the severity of this issue is also expected to grow because of the general worsening of air pollution caused by climate change and the increasing levels of $\text{PM}_{2.5}$ due to an increase in severity of wildfires and area burned (Fiore et al., 2015; Spracklen et al., 2009; Xie et al.,

2020). Therefore, it is important to conduct studies that help us understand the aspects of the role of residential buildings in protecting us against air pollution, in order to support proper adaptation and mitigation actions in the future.

In an effort to comprehend the health benefits achievable by reducing outdoor-origin $\text{PM}_{2.5}$ in residences, D. Zhao et al. (2015) assessed the long-term health and economic impacts of particle filtration using central HVAC systems in 22 locations across the United States. Fisk and Chan have also conducted two studies on the mortality impacts of reducing indoor exposure to $\text{PM}_{2.5}$ using particle filtration. In their first study (2017b), they focused on the cost-benefit analysis of particle filtration interventions via portable filters or installing filters in the central heating and cooling system during a wildfire episode in Southern California. In their second study (2017a), they examined improvements in filter efficiencies in both forced-air heating and cooling systems of homes and HVAC systems of workplaces, as well as the use of portable air cleaners in homes in Los Angeles (CA), Houston (TX), and Elizabeth (Union County, NJ), United States. These studies have all underscored the significant health benefits achievable through improving indoor air quality.

While substantial research has been devoted to understanding the health and economic impacts of interventions aimed at removing particles from the indoor environment, there is a clear need for further exploration into measures that improve building airtightness (air sealing). Such measures can prevent particles from entering the indoor environment in the first place. Moreover, the aforementioned studies are often limited to specific regions or cities, highlighting the necessity for a comprehensive framework that supports analysis at a national scale with fine resolution. This would provide a broader understanding of the impacts across diverse geographical settings.

1.1 Research Statement & Objective

Among the various methods for addressing indoor air pollution, a gap exists in research that evaluates the potential health and economic impacts of enhancing building airtightness on a national scale with fine spatial resolution. Building airtightness directly reduces particle infiltration from outdoor sources (Fisk, 2015). It can thus play an important role in reducing outdoor-origin particles in the indoor environment.

Such studies are highly beneficial, not only for improving human health by reducing exposure to outdoor $\text{PM}_{2.5}$ but also for informing recent energy codes such as International Energy Conservation Code (IECC) and weatherization programs that recommend specific airtightness levels. Understanding the impact of improving airtightness on indoor air

quality can contribute to a more comprehensive understanding of the health implications involved in weatherization programs and retrofit planning (US EPA, 2014).

This research aims to develop a framework that enables the spatial evaluation of air pollution-related health and economic impacts of improving the quality of residential buildings on a national scale. It specifically focuses on PM_{2.5} of outdoor-origin, the impact of airtightness improvements, and single-family homes.

1.2 Research Scope

This study aims to investigate the potential health and economic impacts of enhancing building airtightness levels across the United States from 1980 to 2010. It specifically focuses on single-family homes, which accommodate more than 70% of the population, as improvements in these buildings hold substantial potential for improving public health. This study examines the potential health and economic benefits that could be achieved if single-family homes were made more airtight through various scenarios. These include utilizing mass balance modeling of indoor air pollution, health impact modeling, and economic modeling for assessing national and spatial impacts.

Airtightness levels have recently gained more attention in building codes, primarily due to their significant role in improving building energy efficiency (Poza-Casado et al., 2020). There is also a notable gap between the current residential stock airtightness levels and those recommended in recent codes such as IECC 2018, which call for an average reduction of 79%. One scenario explored involves simulating improvements in building airtightness to bridge the gap between the current stock of single-family homes and the IECC 2018 standards (Section 4.1).

However, addressing the large discrepancy between current airtightness levels and those mandated by codes such as IECC 2018 requires single-family homes to reduce their leakage by an average of 79% to comply. Yet, in practice, airtightness improvement efforts are usually part of energy retrofits, and the literature suggests that the actual leakage reduction achievable through those retrofits typically is less than 30%. Therefore, this study also explores alternative scenarios beyond mere code compliance for a more realistic and comprehensive analysis in the form of sensitivity analysis (Section 4.2).

Additionally, this study incorporates an uncertainty analysis to evaluate the impact of uncertain input variables, providing a more explicit picture of the uncertainty scope within the assessment (Section 4.2.2).

1.3 Thesis Structure

In this chapter, the background, problem definitions, research objectives, and scope were discussed.

Following the introduction, Chapter 2, titled “Background and Literature Review”, provides context for this study. It describes the mass balance, health impact, and economic modeling approaches that form the basis of the framework developed in this study. It also includes essential information and definitions of $\text{PM}_{2.5}$, building airtightness, and building codes, which are vital for understanding this thesis.

Chapter 3, titled “Methods”, details the methodology. It introduces an integrated modeling framework that can be expanded to study the health and economic impacts of indoor air pollution. The framework described is then used to model changes in indoor $\text{PM}_{2.5}$ of outdoor-origin and their health and economic impacts as a result of building airtightness improvements, aligning with the research objective of this thesis. It covers the introduction of data sources and the processing of data for specific applications. Subsequently, the mass balance, health, and economic models are tailored to this use case. Finally, uncertainty modeling is conducted to enable the assessment of the findings’ uncertainties.

In Chapter 4, titled “Results and Discussion”, the results of applying the model developed in Chapter 3 to enhance building airtightness levels to meet IECC 2018 mandates are presented and analyzed. Additionally, a sensitivity analysis on different levels of airtightness improvement levels is conducted, followed by a sensitivity analysis to determine the impact of each uncertain input variable on the results. Finally, a discussion about this study and its findings is formed.

Lastly, Chapter 5, titled “Conclusion and Future Works”, includes the findings and conclusions of this study along with plans and ideas for future work.

Chapter 2

Background and Literature Review

The previous chapter outlined the importance and objectives of this study. The following chapter aims to review the background of the concepts governing this research. In recent years, there has been increased attention to studies focused on indoor air pollution, particularly those examining interventions and their impact on outdoor originated $PM_{2.5}$. Despite this growing focus, numerous gaps remain that need to be addressed, and this study seeks to contribute to a better understanding of this area. Therefore, this chapter first reviews some background on building airtightness. Next, it provides a brief background on air pollutants, specifically $PM_{2.5}$. It then reviews the principles of mass balance modeling of indoor air pollution, common approaches to health impact modeling, and economic modeling.

2.1 Building Airtightness

Airtightness of a building refers to its ability to resist the inward or outward flow of air through its envelope. This air leakage occurs because of differential pressures across the building envelope through gaps and cracks, influenced by stack effects, external winds, and mechanical ventilation systems (Guyot et al., 2010).

Building airtightness is typically measured by the air leakage rate at an applied pressure of 50 pascals, referred to as air changes per hour at 50 pascals (ACH_{50}). This measurement can be converted to air changes per hour under natural conditions by dividing it by a conversion factor that ranges from 16 to 20, as suggested by various studies (Chan et al., 2005; M. H. Sherman, 1987).

The degree of airtightness in a building is typically managed through construction methods used in new builds or deep retrofits in existing structures. Examples of these methods include sealing gaps around windows and doors with sealant materials, repairing damages to window frames, and sealing openings around service pipes and cables that pass through external walls, ceilings, and floors. Additionally, building regulations or standards often specify airtightness requirements as part of energy efficiency regulations, given that airtightness significantly impacts building energy efficiency (Prignon & Van Moeseke, 2017). According to the Office of Energy Efficiency and Renewable Energy of the U.S. Department of Energy (2024), the most widely adopted model energy codes across the United States are the International Energy Conservation Code (IECC) and ASHRAE 90.1, which include specific chapters dedicated to residential building typologies standards. The aforementioned standards also include specific requirements for building airtightness, which older buildings may not meet. Therefore, retrofits can be utilized to bridge this gap and bring older buildings up to current standards.

This thesis concentrates on the impacts of building retrofits aimed at enhancing the airtightness of residential buildings. Accordingly, the remainder of this section introduces the International Energy Conservation Code (IECC), which is the targeted standard for these improvements.

2.1.1 IECC

The International Energy Conservation Code (IECC) sets minimum energy efficiency provisions for commercial buildings and low-rise residential buildings and is one of the most widely adopted codes in the United States; it established the minimum design and construction requirements for energy efficiency. IECC was developed and published by the International Code Council (ICC) for the first time in 2000 and is updated every three years (Office of Energy Efficiency and Renewable Energy, 2024; Doty and Turner, 2004).

IECC includes recommendations and mandates regarding building airtightness, which underwent significant revisions in 2009. Initially, the 2009 code permitted an ACH_{50} up to seven, which was not mandatory if the building passed a visual air barrier inspection after all required items were sealed. In 2012, the code mandated compliance with the air barrier installation table and a follow-up visual inspection, introducing compulsory ACH_{50} levels as well. For climate zones three to eight, the required ACH_{50} was three, while for climate zones one and two, ACH_{50} up to five was permitted. The requirements remained unchanged in the 2015 and 2018 updates. The 2021 code introduced minor modifications, offering more flexibility for buildings in climate zones three through eight, allowing an ACH_{50} up to five in specific cases (Nebbia, 2022).

2.1.2 IECC Climate Zones

The IECC Climate Zones refer to the geographical classification of the United States, as shown in Figure 2.1, made by the International Energy Conservation Code (IECC) based on heating degree days, average temperature, and precipitation that impact buildings' heating and cooling demands. The IECC Climate Zones divide the United States into eight temperature-oriented zones, ranging from Zone 1, which encompasses the warmest regions such as southern Florida and Hawaii, to Zone 8, which covers the coldest areas, including parts of Alaska. Additionally, each zone is further divided based on moisture levels into: moist (A), dry (B), and marine (C). For instance, Zone 3 includes a humid subzone (3A) found in the southeastern states, a dry subzone (3B) in the western states, and a marine subzone (3C) along the Pacific coast. These zones aim to be a guide for improving buildings' energy performance by tailoring construction practices based on the local climate as they dictate many of the energy efficiency measures that a building must include (Baechler et al., 2015; EIA, 2020; Office of Energy Efficiency & Renewable Energy & Energy.gov, n.d.).

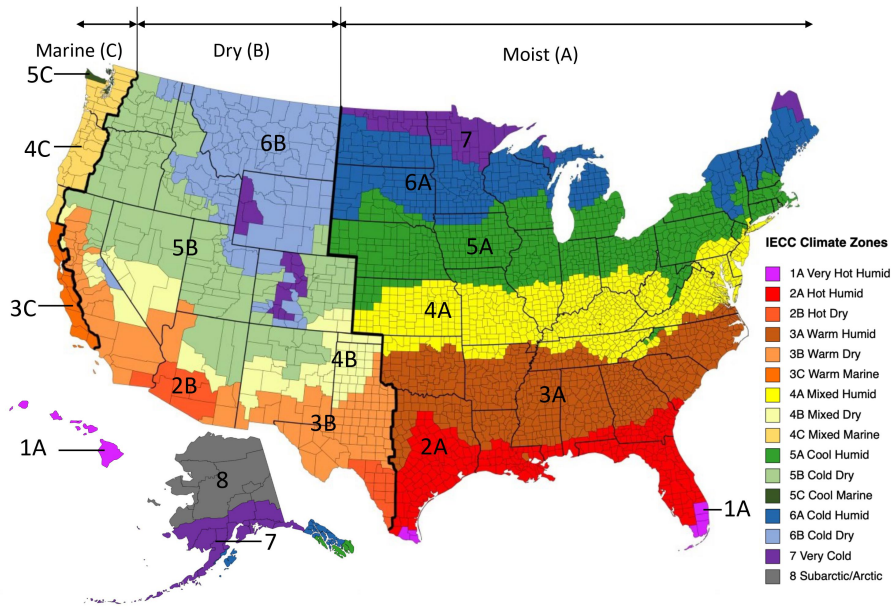


Figure 2.1: Shows the geographical extent of the Climate Zones based on IECC 2021 (ICC, 2021).

2.2 Air Pollution and Fine Particulate Matter

The World Health Organization defines air pollution “as the contamination of the indoor or outdoor environment by any chemical, physical, or biological agent that modifies the natural characteristics of the atmosphere.” Air pollution poses risks to both human health and the environment. Among all air pollutants, both outdoor and indoor exposure to particulate matter, carbon monoxide, ozone, nitrogen dioxide, and sulfur dioxide have significant public health risks, increasing morbidity and mortality rates (WHO, 2024).

Fine particulate matter, known as $PM_{2.5}$, is particularly significant due to its diameter, 2.5 microns or smaller, which allows it to bypass the biological filtration mechanisms of the human respiratory system and to deposit into the organs (Madureira et al., 2020). $PM_{2.5}$ ranks as the fifth leading health risk globally (following: 1. high blood pressure, 2. smoking, 3. high fasting plasma glucose, and 4. high total cholesterol), with a substantial proportion of mortality attributed to it (Cohen et al., 2017). Long-term exposure to $PM_{2.5}$ leads to the accumulation of these particles in the body, resulting in serious health issues. These include an increased risk of cardiopulmonary and ischemic heart diseases, lung cancer, and premature death (Burnett et al., 2018; Krewski et al., 2009; Lepeule et al., 2012).

2.3 Mass Balance Modeling

The levels of indoor pollutants, including $PM_{2.5}$, can be modeled using differential equations. These equations calculate the indoor concentration levels at any given moment, tailored to match the complexity of the available data and the specific use case by accounting for sources and sinks of the pollutant. Equation 2.1 presents a simplified version of these dynamic mass balance equations, inspired by Riley et al. (2002) and Ji and Zhao (2015) where the sources of pollutants are outdoor air and indoor sources, and the only sinks are natural infiltration and deposition rate, assuming no other pollutant removal mechanisms are present.

$$\frac{dC_{in}}{dt} = P \cdot \lambda_{inf} \cdot C_{out} - (\lambda_{inf} + k) \cdot C_{in} + \dot{S} \quad (2.1)$$

Where:

- C_{in} is the indoor concentration of outdoor-origin $PM_{2.5}$ ($\mu g/m^3$) .

- C_{out} is the outdoor concentration of $PM_{2.5}$ ($\mu g/m^3$) .
- P is the penetration factor of the $PM_{2.5}$ through the building envelope (*unitless*) .
- t is the time (*unit of time*).
- λ_{inf} is the air change rate caused by infiltration (*unit of time⁻¹*) .
- k is the coefficient of deposition rate of $PM_{2.5}$ (*unit of time⁻¹*).
- $\dot{S}$ is the volume-averaged indoor $PM_{2.5}$ sources. ($\mu g/(unit\ of\ time \cdot m^3)$).

However, using Equation 2.1 is not ideal for many applications, including the goals of this study, as it requires data with fine temporal resolution, which is often not available. As an alternative, time-averaged mass balance models that assume a well-mixed environment, as shown in Equation 2.2, can be employed for specific use cases. In the context of this modeling framework, and similar studies, where the temporal resolution of the analysis is annual, and the outdoor $PM_{2.5}$ data used are daily averages accumulated over a year, applying the steady-state assumption is appropriate (Abt et al., 2000; Ji & Zhao, 2015; Sparks et al., 2024).

$$C_{in} = \frac{P \cdot \lambda_{inf} \cdot C_{out}}{\lambda_{inf} + k} + \frac{\dot{S}}{\lambda_{inf} + k} \quad (2.2)$$

Where:

- λ_{inf} is the air change rate caused by infiltration (*unit of time⁻¹*) .
- k is the coefficient of deposition rate of $PM_{2.5}$ (*unit of time⁻¹*).
- $\dot{S}$ is the volume-averaged indoor $PM_{2.5}$ sources. ($\mu g/(unit\ of\ time \cdot m^3)$).

As Azimi and Stephens (2020) have noted, the majority of indoor $PM_{2.5}$ exposure originates from outdoor sources. Also, this study focuses on the impacts of airtightness in reducing levels of outdoor-originated $PM_{2.5}$ within indoor environments. Furthermore, as shown in Equation 2.2, the outdoor-originated and indoor-generated $PM_{2.5}$ are linearly independent. This allows for the isolation of the outdoor component of the equation. The infiltration factor (F_{inf}), which represents the ratio of the indoor concentration of outdoor-origin $PM_{2.5}$ to the outdoor $PM_{2.5}$ levels, is then calculated using Equation 2.3 (Fisk & Chan, 2017a, 2017b; Ji & Zhao, 2015; Sparks et al., 2024; D. Zhao et al., 2015).

The infiltration factor enables the study of outdoor-originated $PM_{2.5}$ without requiring to model indoor sources.

$$F_{\text{inf}} = \frac{C_{\text{in}}}{C_{\text{out}}} = \frac{P\lambda_{\text{inf}}}{\lambda_{\text{inf}} + k} \quad (2.3)$$

It must be noted that for a comprehensive study of indoor air quality impacts, the mass balance equation and the infiltration factor equation should be adjusted based on data on hand and the application in mind to include other elements that impact indoor concentration levels. These elements include but are not limited to, indoor air pollutant sources, mechanical ventilation, HVAC systems, air cleaners, etc (Bhoonah et al., 2023; Fisk & Chan, 2017a, 2017b; D. Zhao et al., 2015). While none of these additional complexities are considered in the current study, potential applications are explored in Section 5.2.

2.3.1 Uncertainty

The parameters used in the mass balance equation, which impact the calculation of the infiltration factor (2.3) are uncertain and vary across different situations. Therefore, it is important to account for their uncertainties in any modeling approach. In this section, uncertainties of these parameters are reviewed in more detail. Additionally, building upon what is mentioned in this section, this study’s approach toward uncertainty is explained in the next Chapter in Section 3.2.6.

2.3.1.1 Penetration Factor

The penetration factor represents how effectively pollutant particles of a specific diameter from outdoors can penetrate the building envelope with infiltrating air (Riley et al., 2002). Penetration factor depends on various factors, including but not limited to home characteristics, air exchange rates, occupant behavior, the physical and chemical properties of the pollutants, seasonal effects, and climate (Long et al., 2001; Mosley et al., 2001; Riley et al., 2002; H. Zhao & Stephens, 2017). Therefore, the penetration value differs from building to building, and from time to time. This complexity and wide variation in its value have made it very difficult to model the penetration factor effectively.

Throughout the literature, many studies have tried to estimate the penetration factor value and come up with distributions for this parameter. Also, other studies that rely on the distributions estimated by prior work have included particle penetration factor uncertainties in their models. Here, a quick review of studies that discussed $PM_{2.5}$ penetration

factor and similar studies that tried to account for penetration factor uncertainty in their modeling is presented.

Starting with studies that have estimated penetration factor values, a study by Williams et al. (2003) on residential homes in North Carolina has also come up with a value of 0.71 ± 0.21 based on an analysis of 37 homes. A recent study by H. Zhao and Stephens (2017) uses portable particle sizing instruments and estimates a value of 0.73 ± 0.05 , which is very similar. Continuing with methods employed by works similar to this study to account for penetration factor uncertainty in their mass balance modeling, it can be found that many studies, such as Ji and Zhao (2015) have not accounted for penetration factor uncertainty. Some other studies such as D. Zhao et al. (2015) have recognized variation in penetration factor, but they have used a simplistic approach in accounting for it. They have categorized their buildings based on age into three groups and have assigned a single value to each. They used maximum (1), mean (0.72), and minimum (0.11) values reported by Williams et al. (2003) and assigned them from the oldest to the newest buildings, respectively. Also, two studies from Fisk and Chan have a more systematic approach toward modeling the penetration factor uncertainty. They have combined ranges reported by previous studies together and proposed a truncated normal distribution between 0 (when there is no penetration) and 1 (when windows and doors are open) with a mean of 0.97 and standard deviation of 0.06 (Fisk & Chan, 2017a, 2017b).

2.3.1.2 Deposition Rate

The particle deposition rate is the particle removal rate by sedimentation, adsorption, absorption, etc., on indoor surfaces. It is influenced by particle size, ventilation conditions, and surface to volume ratios thus inhibiting lots of uncertainty (Riley et al., 2002; Wallace et al., 2013; Williams et al., 2003).

The literature contains many efforts to estimate the deposition rate of $PM_{2.5}$. Williams et al. (2003) is one of the most cited studies in that regard. Their results suggest a deposition range value of $0.42 \pm 0.21 (h^{-1})$. A newer study by Wallace et al. (2013) conducted in Canada has significantly different results and suggests a range of $0.99 \pm 0.97 (h^{-1})$ with a median of 0.7. This difference demonstrates the large uncertainty in this parameter.

Additionally, among similar studies to this research, some, such as D. Zhao et al. (2015), despite recognizing uncertainties, have not included them in their model. However, some others, like Fisk and Chan, have assumed a truncated normal distribution with a minimum of 0, a mean of 0.39, and a standard deviation of 0.08 (Fisk & Chan, 2017a, 2017b).

2.3.1.3 Air Change Rate Caused by Infiltration

The air change rate in buildings, caused by infiltration, varies significantly due to numerous factors, particularly the building envelope. The diversity in building envelopes is influenced by location, age of construction, evolving codes and standards, and construction quality. As a result, accurately modeling the air change rate presents complex challenges.

Several studies have endeavored to characterize the air change rates of buildings across the United States, each employing different methodologies and sample sizes. M. Sherman and Dickerhoff (1998), analyzing a substantial sample of 12,646 single-family homes, estimated an average natural air change rate of 1.49 with a standard deviation of 0.73. In contrast, a smaller but more recent study by Williams et al. (2003) reported a narrower range for the natural air change rate at 0.72 ± 0.63 . Chan et al. (2005) took a broader approach by analyzing over 70,000 air leakage measurements to estimate a normalized leakage for buildings across the United States, factoring in variables such as square footage, building age, and household income. They concluded that older and smaller buildings typically exhibit higher normalized leakage rates. Extending this research, Chan et al. (2013) utilized data from 134,000 detached single-family homes in the 'ResDB' database to further refine the characterization of air leakage in the United States housing stock. Their study emphasized the significant role of building age and climate zones in influencing normalized leakage rates.

Moving forward, in reviewing studies that have incorporated air change rates from infiltration into their mass balance equations to estimate indoor air pollution levels, some gaps are evident. Fisk and Chan (2017b) did not account for the uncertainty of air change rates caused by infiltration in their modeling, opting instead for a fixed value of $0.1h^{-1}$. Similarly, D. Zhao et al. (2015) employed whole energy simulation software to estimate annual averages for air change rates due to infiltration but did not perform an uncertainty analysis concerning this parameter.

This thesis has adopted a novel approach to account for the uncertainties in air change rates caused by infiltration compared to similar studies, addressing the variabilities across different locations and building ages. This approach is thoroughly explained in Sections 3.2.2.2 and 3.2.6.

2.4 Health Impact

To evaluate the health impacts of air pollution on the population, health impact (H-I) functions, which include Concentration Response (C-R) Functions, can be utilized to relate

exposure to air pollution to increased risk of mortality or morbidity. They statistically estimate the increase in health risk on a population level by relating additional cases of death or diseases caused by a higher exposure of a given population to air pollution. The H-I functions have inputs in terms of the baseline health condition of the population of interest, changes in air pollution levels, and the C-R function of interest from epidemiology studies to estimate the excess risk and the attributable excess incidences (additional cases caused by exposure increase). H-I functions can be written in different forms, such as log-linear as Equation 2.4 (Fann et al., 2012) or linear as shown in Equation 2.5 (Anenberg et al., 2010).

$$\Delta Y = Y_0 \cdot (1 - \exp^{-\beta \cdot \Delta C_{out}}) \quad (2.4)$$

$$\Delta Y = Y_0 \cdot \frac{RR - 1}{RR} \cdot \frac{\Delta C_{out}}{10\mu g/m^3} \quad (2.5)$$

Where:

- Y_0 is the baseline mortality rate (*incidence per persons*).
- ΔY is the change in the mortality rate (*incidence per persons*).
- ΔC_{out} is the change in outdoor air pollution concentration levels ($\mu g/m^3$).
- β is the risk estimate in the form of risk coefficient from epidemiology studies ($\frac{1}{\mu g/m^3}$).
- RR is the risk estimate in the form of relative risk from epidemiology studies (*unitless*).

These two forms of H-I functions result in approximately similar results for small ΔC_{out} since RR and β are converted to each other by Equation 2.6 (Azimi & Stephens, 2020).

$$\beta = \frac{\ln(RR)}{10\mu g/m^3} \quad (2.6)$$

Also, to obtain total health outcomes for the entire population, Equation 2.7 can be used.

$$\Delta Outcomes = \Delta Y \times Pop \quad (2.7)$$

Where:

- $\Delta Outcomes$ is the total health outcomes (*incidence*).
- Pop is the population (*persons*).

In the rest of this section, traditional C-R functions, which are designed to input changes in outdoor air pollution concentrations to evaluate risks, are explained, and then modified C-R functions, which input indoor changes in air pollution concentration levels, are discussed.

2.4.1 Traditional Concentration Response Functions

The traditional C-R functions estimate changes in health risk based on changes in outdoor air pollution concentration levels. They are established based on epidemiology studies (such as Krewski et al. (2009) and Lepeule et al. (2012)) that have examined the sensitivity of mortality to changes in monitored outdoor PM_{2.5}. In other words, they assume that changes in outdoor levels of air pollution concentration are representative of the population's exposure change to air pollution. For instance, Lepeule et al. (2012) reported a relative risk of 14% for every 10 ug/m^3 increase in outdoor PM_{2.5} levels, and Krewski et al. (2009) has reported a relative risk of 6% for every 10 ug/m^3 increase in outdoor PM_{2.5} levels. As previously mentioned, the underlying reason for the health impact is the total exposure to air pollution, and the C-R functions resemble impacts of exposure change. However, because outdoor air pollution is a public good and the necessity of regulating it draws researchers' attention, and also because it is a variable that is easier to measure and track, it is used as a metric instead of the total exposure in epidemiology studies.

As mentioned, since traditional C-R functions are derived to operate with outdoor air pollution levels, it is incorrect to plug indoor air pollution levels directly into them. The next part explains solutions proposed by indoor studies to adjust C-R functions.

2.4.2 Indoor Studies and Concentration Response Function

As stated in Chapter 1, most exposure of Americans to PM_{2.5} occurs in environments other than outdoors, specifically within buildings; therefore, it is crucial to study indoor air quality and the factors that impact indoor levels of PM_{2.5}. However, it is incorrect to apply changes in indoor levels of outdoor PM_{2.5} directly to traditional C-R functions because, as mentioned, indoor exposure constitutes only a portion of the total exposure, and this approach leads to an underestimation of the final result.

Previous studies in the literature have also identified this issue and recognized that indoor changes in pollution of outdoor-origin cannot be interchangeably used with outdoor concentration levels. The literature first tried to estimate the health impacts attributable to indoor exposure to outdoor-origin pollution, and their efforts then evolved in the approaches to estimate the health impacts of changing indoor air pollution levels of outdoor-origin.

Logue et al. (2012) is one of the pioneers in this field, noting that the portion of exposure related to residences is proportional to the time spent there. Their approach aimed to estimate the health impacts attributable to indoor exposure to pollution of outdoor-origin; however, it is quite basic and does not consider infiltration factors. D. Zhao et al. (2015) attempted to quantify the health impacts of changes in indoor air pollution of outdoor-origin by modifying β to include the infiltration factor of residences, stating that the equivalent levels of indoor changes in terms of outdoor pollution are calculated as shown in Equation 2.8. However, their methodology did not account for the time spent in different micro-environments or the infiltration factors of other environments. Azimi and Stephens (2020) built upon the approaches of Louge and Zhao by incorporating infiltration factors and the time fraction spent in different environments to adjust β for calculating health outcomes attributable to indoor exposure to outdoor-origin pollution. Inspired by Azimi and Stephens (2020), this study has expanded their methods to calculate health impacts due to changes in indoor air pollution. The approach of this study is detailed in Section 3.2.4.

$$\beta_{modified} = \frac{\beta}{F_{inf}} \quad (2.8)$$

Where:

- $\beta_{modified}$ is the modified risk coefficient (*unitless*).
- F_{inf} is the infiltration factor of residences (*unitless*).

2.4.3 Health End Point Estimate Uncertainty

The health endpoint estimates (β or Relative Risk) are highly uncertain due to variations across populations and locations. Modeling these uncertainties presents challenges because each epidemiological study that estimates a health endpoint has its own range and level of uncertainty, and different studies yield different ranges.

To address this variability, some studies perform sensitivity analyses based on different epidemiological studies (Saari et al., 2019; D. Zhao et al., 2015), while others use pooled estimates to capture a broader spectrum of possibilities (Azimi & Stephens, 2020; Saari et al., 2019).

For instance, mortality health endpoint estimates in terms of increase of relative risk for long-term exposure to $10\mu g/m^3$ of outdoor $PM_{2.5}$, commonly cited in the literature include Pope et al. (2002), which reports a 5.8% increase (3.3%, 8%), situated at the lower bounds, situated in the higher end, Laden et al. (2006) notes a 15% increase (7%, 26%), and Fann et al. (2016) provides a pooled estimate of 7.03% (3.7%, 11%), based on the literature.

2.5 Health Benefits

Adverse health incidences, including disease and death, have a toll on the economy. These economic impacts can be tangible (market effects), like medical costs, lost productivity, and lost wages or they can be non-tangible (non-market effects) like pain and suffering. There are different approaches to account for the economic valuation of health endpoints, such as the lost income approach or the regulatory approach using willingness-to-pay (WTP). While the lost income approach may be unsuccessful in capturing the whole economic impact, the WTP approach aims to capture both tangible and intangible effects (Saari et al., 2017; US EPA, 2017).

The estimates of WTP can then be used to quantify the benefits of avoiding health risks. Among all estimated values of WTP for various health endpoints and air pollution-related health outcomes, avoided premature mortality is predominant, accounting for more than 90% of the economic benefits. Therefore, the estimate of WTP associated with reducing mortality risk has received significant attention (Saari et al., 2015; Viscusi et al., 2018). This quantity is commonly called the Value of a Statistical Life (VSL).

Defined by the US EPA (2017), the VSL represents the amount a population is prepared to spend to marginally decrease the likelihood of premature mortality. It is important to clarify that VSL is not a direct valuation of human life or the cost to avert inevitable death but a statistical measure reflecting minor risk adjustments (Cameron, 2010).

The VSL then is used to calculate the economic benefits of air pollution related to avoided premature mortality as shown in Equation 2.9.

$$Benefits = \Delta Mortality \times VSL \quad (2.9)$$

2.5.1 VSL Value and Uncertainty

VSL varies across populations and is influenced by variables such as income. The Environmental Benefits Mapping and Analysis Program (BenMAP), which is an open-source tool for air quality health and economic impact assessment from EPA, has accounted for these variations and uncertainties (Sacks et al., 2018). BenMAP previously included several distributions representing the VSL and associated uncertainties (EPA, 2017). However, in its most recent version (EPA, 2023), it has incorporated only one Weibull distribution, fitted on 26 VSL studies that exist in the economic literature, with a scale parameter 9,648,168 and a shape parameter of 1.51, and a mean value of \$8,705,114 in 2015 USD (Figure A.6).

Chapter 3

Methods

In Chapter 1, the significant adverse effects of exposure to indoor air pollution, specifically PM_{2.5}, were explained in detail. It was also mentioned that studying and understanding factors that impact the quality of air in our houses is important and can help decision-makers garner a broader perspective on air pollution exposure. Also, upon reviewing the literature, a lack of a study that evaluates the air pollution related health and economic impacts of improving building airtightness was noticed. Therefore, this study aims to develop an integrated modeling framework that enables the cost-benefit analysis of air pollution related health impacts of improving building airtightness and enables spatial analysis on a national scale.

In Chapter 2, the background of models used to develop this study's integrated modeling framework was reviewed for context, including approaches toward mass balance modeling of indoor air pollution concentration levels, the epidemiology functions for evaluating health impacts, and the economic functions for assessing economic cost-benefits. In this section, an overview of the developed framework is provided first, and then the implementation of the framework to study the economic and health impacts of changes in exposure to outdoor-origin PM_{2.5} due to airtightness improvements of single-family homes in the United States is explained in detail.

3.1 Overview of the Integrated Modeling Framework

Figure 3.1 conceptualizes the integrated modeling framework created in this study to assess the air pollution related health and economic impacts of improving building airtightness. The figure highlights the main elements and procedural steps of the model, and the goals it tries to achieve. It begins with highlighting the residential stock, which is used to establish the basis of the analysis by setting the baseline airtightness levels of the residential stock and determining the airtightness levels after intervention, setting an alternative state. It then shows that changes in building airtightness translate to deviation in indoor concentration levels of outdoor-origin $\text{PM}_{2.5}$ between the baseline and the alternative states, which leads to population change in exposure to $\text{PM}_{2.5}$. Subsequently, the health and economic impact assessment component integrates these exposure changes, translating them into quantifiable health outcomes and economic net benefits. Finally, the outcomes of this study contribute to the evaluation of policies from the perspective of connecting health, indoor air quality, and building airtightness, and help the understanding of how future building regulations can impact public health systematically.

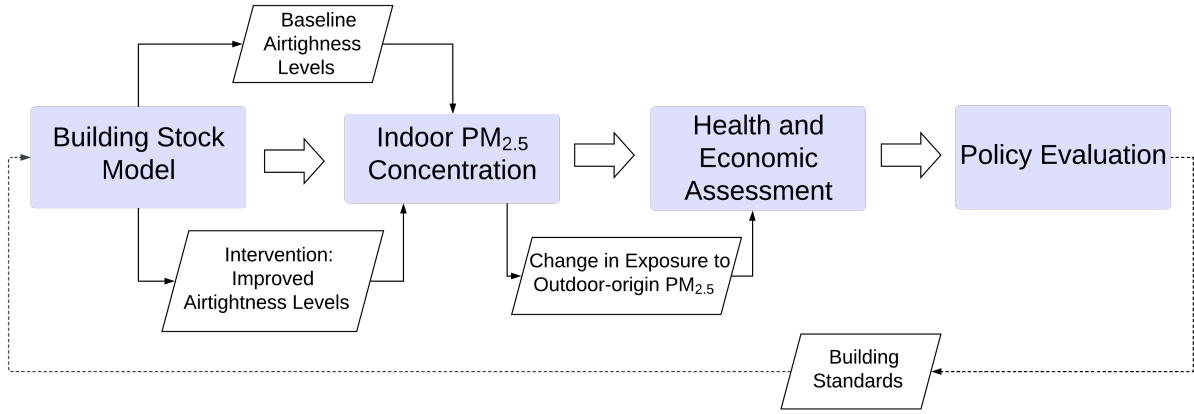


Figure 3.1: Conceptualises the main elements of the integrated modeling framework developed and its implications.

3.2 Implementation of the Integrated Modeling Framework

In this section, the implementation of the integrated modeling framework created during this study to assess health and economic impacts of reducing the infiltration of outdoor-origin PM_{2.5} in residential buildings due to improved airtightness levels is described in detail. This includes defining the spatial scope of the study, explaining the data gathering and processing step, explaining the intervention and mass balance modeling, health impact modeling, and economic modeling, and finally, uncertainty modeling.

Figure 3.2 presents a flow chart that summarizes the entire framework, highlighting the main inputs, processes, and outputs of the modeling framework. It aims to abstract the model and facilitate understanding. The elements visualized will be detailed in the following sections.

While developing this methodology and implementing it using the Python programming language, as outlined in the scope of this thesis (Section 1.2), there was a focus on making the framework modular and adaptable for studying a wide range of scenarios with minimal changes to the model inputs. The methodology, visualized in Figures 3.1 and 3.2 and detailed in this section, can be easily adapted to model and evaluate the health and economic impacts of changes in population exposure to specific indoor air pollutants due to building interventions. The framework supports analysis at any spatial scale, down to county-level resolutions, provided the appropriate data are inputted. While a comprehensive description of the developed Python tool extends beyond this thesis, the scripts created for this framework during the study are accessible via GitHub ([Link¹](https://github.com/AmirrezaSLH/MASc_Health_and_Economic_Building_Improvement_Air_Pollution)); the data used is also available in the same repository. The materials in the GitHub repository and the explanations provided in Figure 3.2, together with descriptions provided in the rest of this section and Sections 2.3, 2.4, and 2.5, serve as guidelines for adapting the framework to other use cases.

¹https://github.com/AmirrezaSLH/MASc_Health_and_Economic_Building_Improvement_Air_Pollution

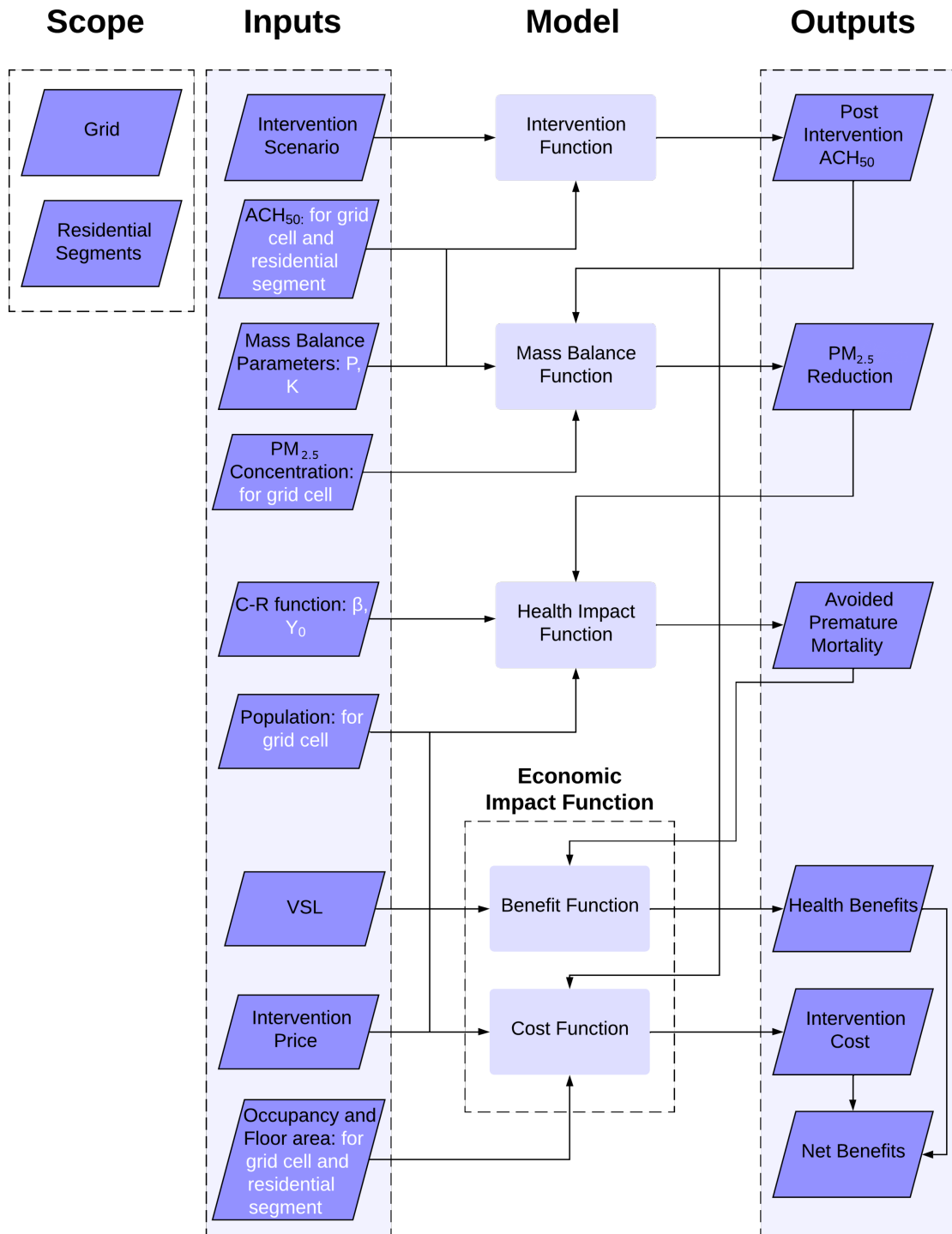


Figure 3.2: Flow chart serving as a visual guide to understanding the structure of the modeling framework, highlighting its primary inputs, processes, and outputs.

3.2.1 Spatial Scope

The spatial extent of this analysis covers the contiguous United States, and the resolution of the analysis is defined on grid cells measuring $1.9^\circ \times 2.5^\circ$. The main reason for choosing this grid resolution was to enable the framework to use the Community Atmosphere Model with Chemistry referred to as CAM-Chem (Lamarque et al., 2012) simulations conducted on this grid by previous work of our research group (Saari et al., 2019; Sparks et al., 2024). This grid resolution also enables the study of futuristic scenarios in our research group's future studies since modeled air pollution data is available for this resolution. Figure 3.3 demonstrates a graphical representation of the grids.

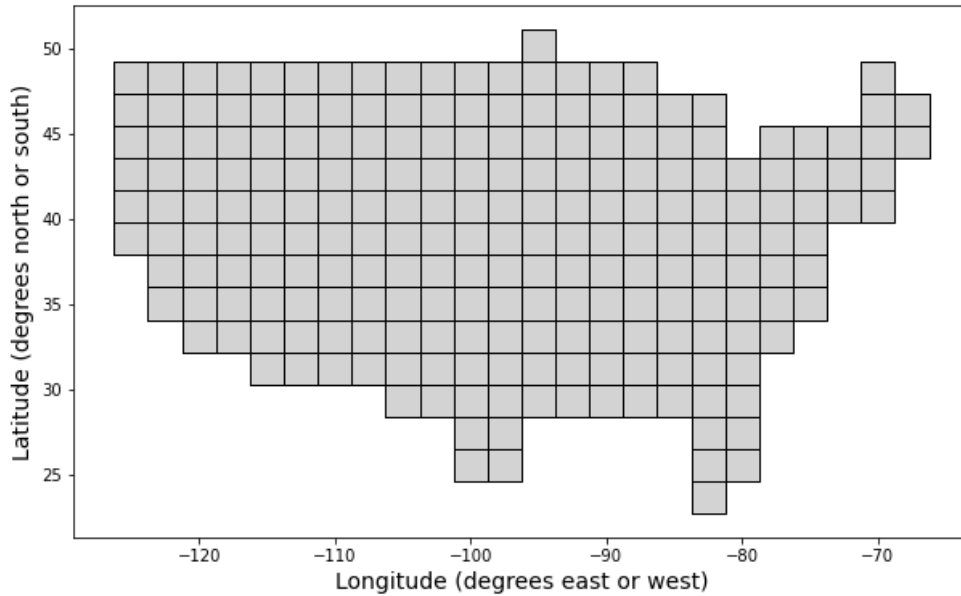


Figure 3.3: Illustrates the spatial resolution of the study grid, contiguous United States with a resolution of $1.9^\circ \times 2.5^\circ$ cells.

3.2.2 Data Gathering and Processing

The next step after setting the spatial scope and resolution of the model, was gathering and processing the required data at the defined resolution of $1.9^\circ \times 2.5^\circ$. The data required and utilized in the modeling approach includes outdoor annual $\text{PM}_{2.5}$ daily average values, building stock information, population data, health function parameters, the Value of a

Statistical Life (VSL), and building airtightness improvement costs. Here, the sources of each of these parameters and the approaches used to process them are explained.

3.2.2.1 Air Pollution

This study’s pollutant chosen for analysis is fine particulate matter (PM_{2.5}). The daily modeled PM_{2.5} concentration in $\mu g/m^3$ from prior work conducted by our lab between the years 1980 to 2010 was obtained (Saari et al., 2019). Then, since the temporal resolution of the study is annual, the annual daily average concentrations were calculated per grid cell for the analysis period (start of the century), and the analysis was carried out based on that.

3.2.2.2 Buildings Stock

To be able to reflect and model the impacts of airtightness improvements spatially across the United States, essential information on attributes such as building infiltration across different locations is required. Then that information should be processed per grid cell to create a representation of the whole stock.

The building stock information was collected from a dataset called ResStock, which is part of the U.S. Buildings Characteristics Studies conducted by the National Renewable Energy Lab (NREL) and Rocky Mountain Institute. This dataset is designed to be representative of buildings across the United States. It contains over half a million building samples, representing approximately 0.5% of all residential buildings in the United States. It includes information on almost 270 different building attributes, including many important building characteristics like building location with county resolution, building climate zones, building construction decade, and building air change rate measured in units of ACH_{50} , floor area in square feet, and occupancy. Additionally, other useful information contained in this dataset, such as building ventilation, HVAC systems, and heating and cooking fuels, can be utilized in further indoor air pollution research (Reyna et al., 2022). To understand the dataset and facilitate the optimal use of the information it contains, an exploratory analysis was conducted, which is presented in the following section.

3.2.2.2.1 Exploratory Analysis

This section presents ResStock data in order to obtain a better understanding of the information at hand. Also, this descriptive exploratory analysis, which encompassed data visualization as well as grouping and aggregation summaries, supports some design decisions

made using the modeling approach. After reviewing the attributes available, those deemed relevant to the purpose of this study—analyzing airtightness improvements—were selected for further examination. These attributes were building type, building age reported in the decade constructed, building size in square feet, building infiltration in ACH_{50} , occupancy, building location with county resolution, and building climate zone.

As this study uses ResStock to spatially model residential buildings across United States, the initial step of the exploratory analysis was to verify whether the dataset accurately represents the stock of residential buildings in the United States and has enough diversity to represent different buildings.

Many building characteristics, especially building airtightness, are correlated with the building construction date (Chan et al., 2013); therefore, the hypothesis that ResStock has enough variations among different age groups was tested. Figure 3.4 shows the prevalence of different age groups in buildings across all building types, as it can be seen there is a fair number of each age group among all building types.

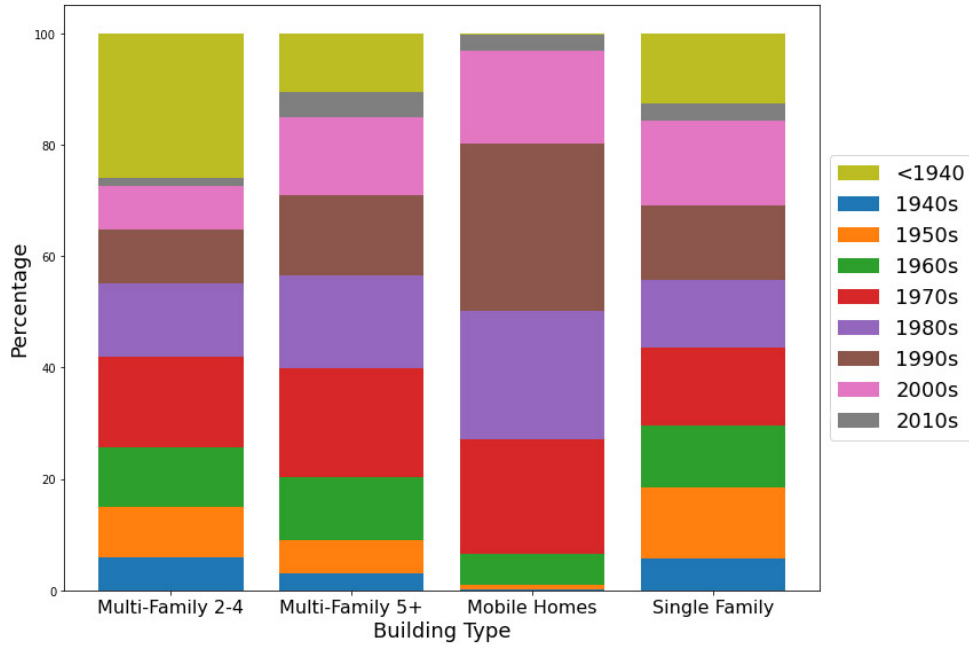


Figure 3.4: Shows the spread of ResStock’s samples from each decade across building types.

The hypothesis that the distribution of building samples in ResStock across different types and ages accurately represents the actual building stock was tested by comparing

the proportion of samples in ResStock with data from the U.S. Census Bureau (2024). A negligible discrepancy (less than 4% in all segments) between ResStock and the U.S. Census data concerning the percentage of buildings within each type and construction decade concluded that ResStock is suitable for modeling the residential building stock of the United States.

After reviewing the attributes available in ResStock in search of parameters that can be used to model buildings' airtightness, ACH_{50} was chosen to represent building airtightness and to calculate the infiltration factor. The literature has suggested specific behaviors for buildings' airtightness levels and infiltration based on their location and age. The next main step in the exploratory analysis was to test if the ACH_{50} values of the samples in ResStock were consistent with the literature or not. Previous studies mention that building infiltration varies based on location and that buildings in warmer and humid regions are generally leakier than those located in colder and dry climates. Also, newer buildings generally tend to be less leaky than older ones (Chan et al., 2013). The following Figures 3.5 through 3.7 are created to test the hypothesis that ResStock patterns in ACH_{50} values are aligned with the literature.

As can be seen in Figure 3.5, older buildings are leakier and also there is a pattern showing buildings in warmer and more humid climate zones are leakier. This supports the hypothesis that ResStock ACH_{50} levels of buildings follow a similar pattern as suggested in the literature.

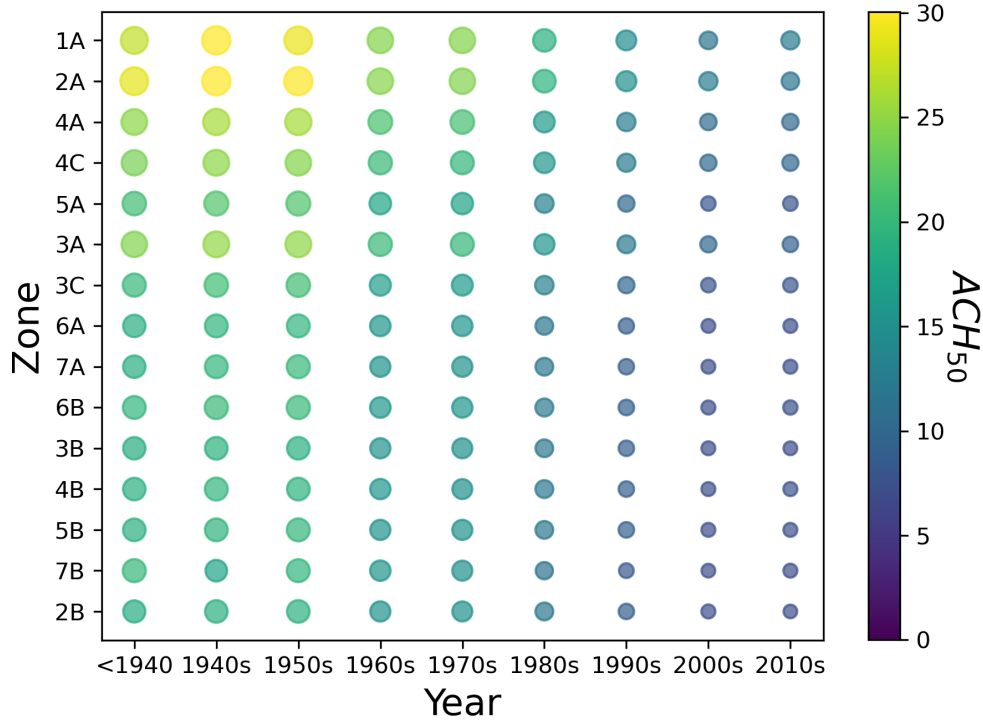


Figure 3.5: Shows the relative mean of ACH_{50} levels for ResStock’s buildings of different age groups across climate zones.

The exploratory analysis identified the ACH_{50} attribute as representative of the building’s airtightness. Additionally, it was validated that ResStock provides a representative sample of the United States residential sector, and the ACH_{50} values across the sample are consistent with those reported in the literature.

3.2.2.2.2 Segmentation

For a more accurate analysis of the impacts of improvement of buildings’ airtightness on human health, it is required to segment residential buildings to smaller groups with more similar airtightness characteristics.

ResStock has recommended building segmentation based on type and construction date,

noting the similarity of most building characteristics within this categorization. The proposed building types include Single-Family Homes, Multi-Family with 2–4 units, Multi-Family with 5+ units, and Mobile Homes, categorized by construction vintage: pre-1940 (Vintage 1), 1940–1980 (Vintage 2), and post-1980 (Vintage 3) and by location. However, it was required to justify the applicability of this segmentation model for this study’s applications. The main purpose of this study is to analyze airtightness levels, specifically single-family homes; therefore, the hypothesis that the ACH_{50} values across the recommended segmentation also is meaningful for the ACH_{50} attribute across building segments was necessary.

To test the hypothesis that ACH_{50} follows a meaningful pattern based on building type, age, and location (climate zone), Figures 3.6 and 3.7 were created. Figure 3.6 not only shows that the older buildings from a specific type are less airtight, it also shows that there is a clear separation between them across all age groups. Figure 3.7 also shows that the difference between different building types is consistent across different climate zones and shows building climate zone (location) is a very important measure because the change in climate zone impacts all types of buildings and reinforces the assumption that buildings’ airtightness has a dependency on climate zones.

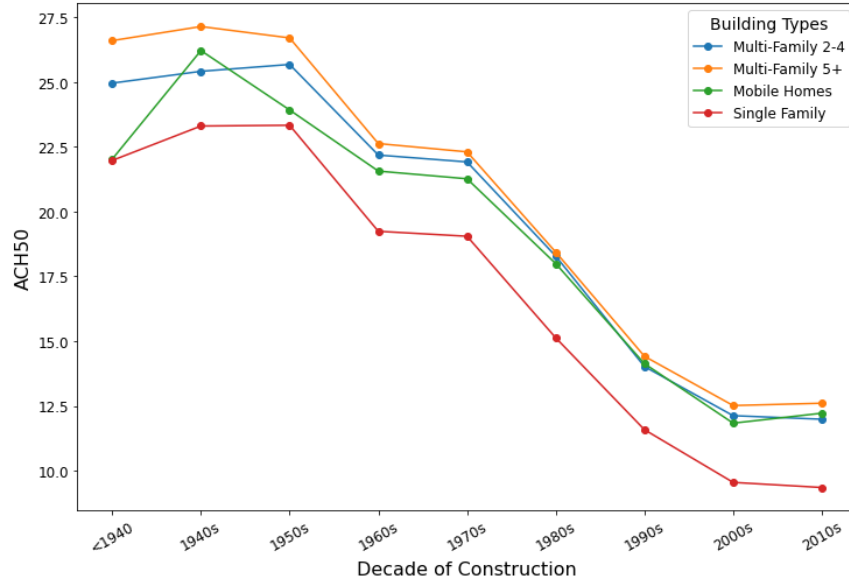


Figure 3.6: Shows the mean ACH_{50} levels of ResStock’s different building types across different construction decades.

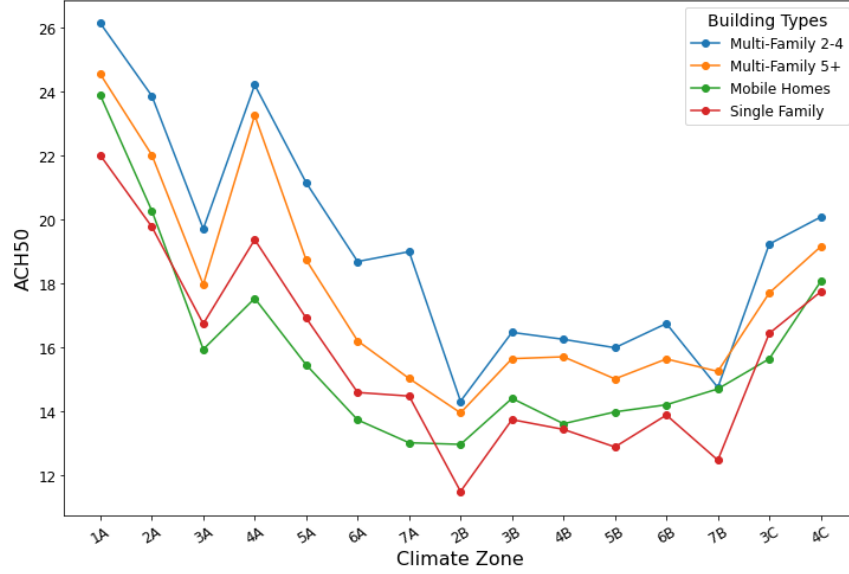


Figure 3.7: Shows the mean ACH_{50} levels of ResStock’s different building types across different climate zones.

As demonstrated, residential buildings’ airtightness, as represented by ACH_{50} levels, varies significantly across different building types, age, and climate zones (location). The patterns observed in the figures underscore the importance of proper segmentation for targeted intervention analysis, particularly in single-family homes. Furthermore, the consistent impact of climate zone (location) on airtightness across all building types highlights the importance of evaluating improvement strategies that are location-specific. This analysis justifies the segmentation approach recommended by ResStock and reinforces the necessity of considering building type, age, and geographic factors in efforts to model residential airtightness levels.

3.2.2.2.3 Stochastic Sampling

The next step is obtaining a representative value for parameters that are required for mass balance modeling, as well as a cost-benefit analysis for each segment and location. Therefore, using ResStock, this study estimated a representative distribution of average values of ACH_{50} , floor area, and occupancy for each of the 12 segments per study grid cell. Acknowledging the dataset’s comprehensive coverage of United States residential stock, the study explored various strategies to accurately determine these representative

values, thereby enhancing the precision of calculations of indoor $\text{PM}_{2.5}$ concentrations of outdoor-origin and cost-benefit analysis on a grid-cell basis. Given this context, multiple methodologies were employed to compute these representative values, aiming to identify the most accurate approach. Here, the chosen methodology is explained.

Starting with the available data and identifying what is necessary, ResStock provides information on the location of sample buildings with county-level resolution. This means that for each county, there are sample buildings from which the average values for ACH_{50} , floor area, and occupancy can be calculated per residential segment. However, this study requires these average values at the resolution of grid cells, which are larger than counties. One method to obtain average values at the grid cell level would be to identify all counties within a grid cell and perform the calculations for all buildings therein. The challenge arises when counties intersect multiple grid cells (as shown in Figure 3.8), complicating the assignment of buildings to a specific grid cell.

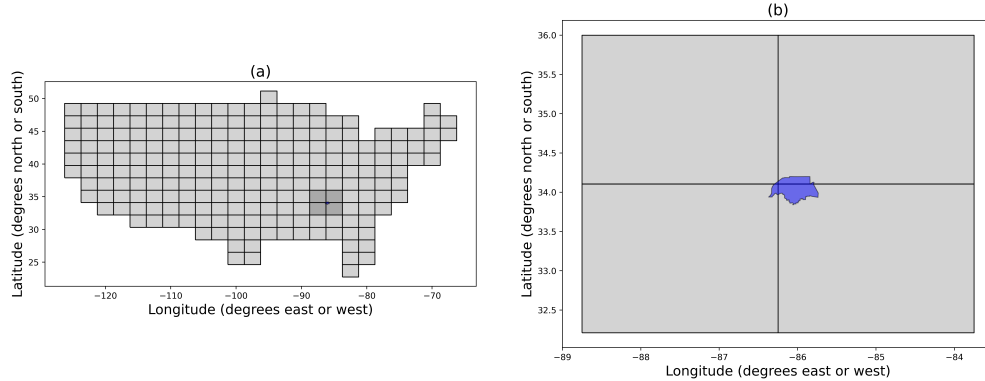


Figure 3.8: Displays an example of a county intersecting multiple grid cells. Subplot (a) highlights the four grids intersecting with a given county, and subplot (b) provides a magnified view of this intersection.

The methodology used here aims to solve the mentioned problem and involves allocating building data to corresponding grid cells, particularly in cases where counties intersect

multiple cells. Figure 3.9 includes a schematic of the algorithm used. Initially, the proportion of a county's area within each grid cell is calculated for counties intersecting with multiple grid cells, which is crucial for subsequent allocation of building samples. Buildings in counties entirely within one grid cell are directly assigned, while those spanning multiple cells use a stochastic sampling method based on the relative area within each cell. An average occupancy, and weighted averages for ACH_{50} and floor area, are then calculated for each grid cell, considering the varying number of occupants across buildings. Considering computation time, output file size limitations, and negligible marginal changes in distributions with increased iterations, this iterative process is repeated only 100 times to generate a comprehensive distribution of the averages of ACH_{50} , floor area, and occupancy of each building segment per grid cell.

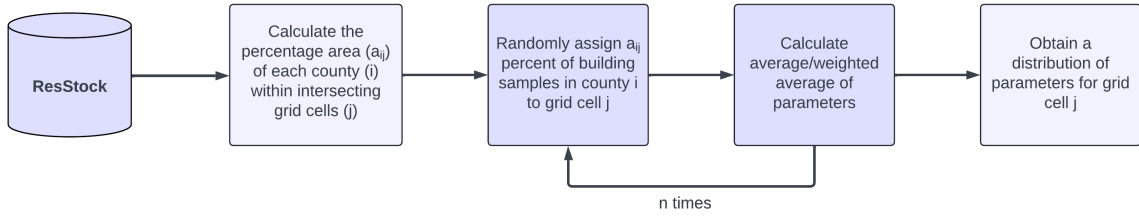


Figure 3.9: Illustrate the stochastic resampling from ResStock to create representative distributions for buildings attributes for each grid and segment.

Examples of the distributions generated by this algorithm for ACH_{50} , floor area, and occupancy for single-family homes are shown respectively in Figures 3.10, 3.11, and 3.12.

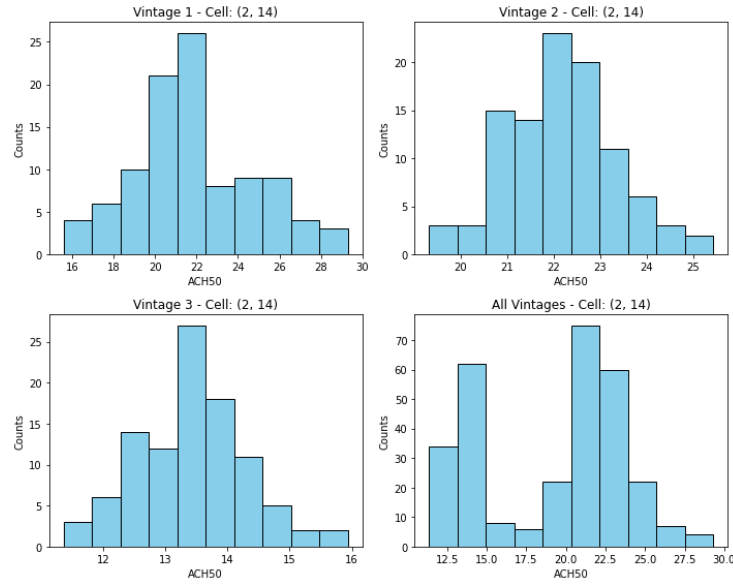


Figure 3.10: Displays the mean ACH₅₀ distributions for all vintages of single-family homes, generated by stochastic sampling from ResStock, for grid cell (2, 14) as an example.

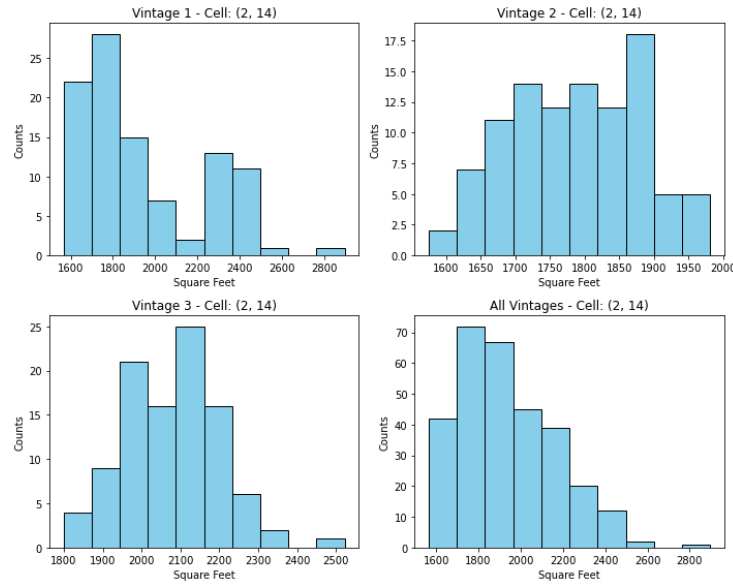


Figure 3.11: Displays the mean floor area distributions for all vintages of single-family homes, generated by stochastic sampling from ResStock, for grid cell (2, 14) as an example.

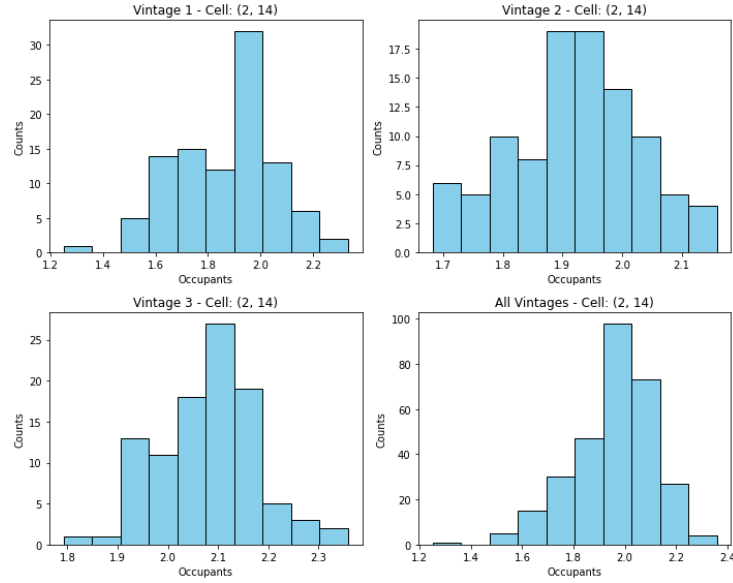


Figure 3.12: Displays the mean occupancy distributions for all vintages of single-family homes, generated by stochastic sampling from ResStock, for grid cell (2, 14) as an example.

As detailed in Section 3.2.6, these distributions are employed to propagate uncertainty in mass balance modeling and cost estimation within the model.

3.2.2.3 Population

The population information and the baseline mortality rates used in this study are based on BenMAP-CE (Sacks et al., 2018) and are gathered from previous work, conducted by our lab (Saari et al., 2019; Sparks et al., 2024) that have processed the information for each grid cell, under the start of the century period between 1980 to 2010.

3.2.2.4 Health Impact Function

For this study, a modified C-R function is derived as explained in Section 3.2.4 based on a log-linear form of the C-R function as shown in Equation 2.4 and a β value from Krewski et al. (2009) as explained in Section 2.5.1.

3.2.2.5 VSL

The VSL data for this study and uncertainty propagation is gathered from the latest BenMAP-CE version 1.5.11 (EPA, 2023) and is explained completely in Section 2.5.1.

3.2.2.6 Costs

The process of improving building airtightness is complex and dynamic, involving a range of different measures, some aimed directly for the purpose of improving airtightness and reducing infiltration and others as indirect effects of other interventions. Consequently, quantifying the exact costs associated with enhancing airtightness is challenging. A study by Lawrence Berkeley National Laboratory (LBNL) focused on the costs of retrofitting has also devoted a section to air sealing costs. This study aimed to compile national data on the costs of home energy retrofit projects along with their impact on household energy performance. It utilized a dataset comprising 1739 projects across 15 states, associated with 12 energy programs and including 10512 individual measures. As part of its results, since airtightness has a significant impact on energy performance, they also had analyzed airtightness changes and associated costs. It noted that the costs related to improving building airtightness are influenced by multiple factors and are very complicated to estimate directly. Therefore, the report did not specify costs per individual measure; rather, instead, it reported an estimated expected cost per unit area as a result of a combination of all measures taken to enhance air sealing; in relation to the percentage reduction in air leakage.

This report includes eight national average cost values in 2019 USD for specific leakage reductions, from 10% to 80% reduction levels, as shown in Figure A.1. These data points have been utilized to model costs in this study. The process involves cleaning and fitting regression models to this data, enabling the estimation of costs for reduction points beyond the initial eight. For each of these points, median, maximum, and minimum values are available. After excluding the data points of the 70% and 80% leakage reductions as outliers using visual inspection and the Interquartile Range (IQR) method, linear regression was applied to the median ($R^2 = 0.985$), minimum ($R^2 = 0.912$), and maximum ($R^2 = 0.864$) values, as shown in Equations 3.1, 3.2, and 3.3 respectively. A visual representation of the regressions is also available in Figure A.2. Detailed information on how these data are used in the model can be found in Sections 3.2.5.2. Additionally, this approach facilitates the creation of distributions that represent the associated uncertainty, as explained in Section 3.2.6.

$$P_{\%R\lambda}^{median} = 0.0085 \times \%R\lambda + 0.1693 \quad (3.1)$$

$$P_{\%R\lambda}^{min} = 0.0044 \times \%R\lambda + 0.16 \quad (3.2)$$

$$P_{\%R\lambda}^{max} = 0.0104 \times \%R\lambda + 0.266 \quad (3.3)$$

Where:

- $\%R\lambda$ is the percentage of building leakage reduction.
- $P_{\%R\lambda}^{median}$ is the median price for $\%R\lambda$ leakage reduction ($USD/sqft$).
- $P_{\%R\lambda}^{min}$ is the minimum price for $\%R\lambda$ leakage reduction ($USD/sqft$).
- $P_{\%R\lambda}^{max}$ is the maximum price for $\%R\lambda$ leakage reduction ($USD/sqft$).

3.2.3 Intervention

The implementation of the modeling framework started with defining the spatial scope and resolution of the model and continued by gathering and processing data to set up model parameters. The next main step intends to establish the means to achieve the study objective which is evaluating the impact of improving single-family homes' airtightness levels on indoor air quality and human health. This step consists of defining a building improvement measure, referred to as an intervention, which deviates the residential stock airtightness level from its initial state.

To evaluate the health impacts and, consequently, the economic impacts of different intervention measures using health impact functions, it is necessary to calculate the changes in the indoor concentration level to which the population is exposed. To do so, first, the baseline indoor PM_{2.5} concentration levels and then concentration levels after intervention in the building stock should be estimated. In this section, the modelling of baseline state indoor PM_{2.5} levels of outdoor-origin and its post-intervention levels is explained

3.2.3.1 Baseline State

The baseline state refers to the indoor PM_{2.5} levels of outdoor-origin when no changes have been applied to the building stock. The main purpose of this section is to propose a way to estimate the baseline indoor concentration of outdoor-origin PM_{2.5} to which Americans are exposed.

Building upon the governing equations outlined in Section 2.3 for determining indoor concentration levels of outdoor-origin PM_{2.5}, this section introduces the model applied in this study. In the first step, a method to calculate the average PM_{2.5} concentration across all residences is required. To do so, the representative values of ACH₅₀ obtained in Section 3.2.2.2 for each residence segment per grid cell are used to calculate mean indoor concentrations for that residence segment, as shown in Equations 3.4 through 3.6.

Equation 3.4 converts air change per hour at 50 Pa pressure differential to air change per hour under conventional conditions, where CF is a conversion factor for converting ACH₅₀ to natural ACH. There are different values for CF reported in the literature, but commonly, studies tend to refer to two studies; an older study has suggested a conversion factor of 20 (M. H. Sherman, 1987), but a newer study which was used as the conversion factor here has suggested a value of 16 (Chan et al., 2005).

$$\lambda_{r,g} = \frac{ACH_{50}}{CF} \quad (3.4)$$

Equation 3.5, derived from the mass balance equation adapted for this use case, calculates the infiltration factor of outdoor PM_{2.5} into buildings in segment r and grid cell g .

$$F_{r,g} = \frac{\lambda_{r,g} \cdot P}{\lambda_{r,g} + k} \quad (3.5)$$

However, as $F_{r,g}$ represents buildings of segment r located in grid cell g , it is crucial to account for variations and uncertainties among different buildings. The uncertainties discussed are linked to the inputs of the function, including the penetration factor, deposition rate, and natural infiltration. The method for modeling these uncertainties is detailed in Section 3.2.6.

After obtaining the indoor PM_{2.5} of outdoor-origin concentration inside each resident segment across all grid cells, the next step is determining how much the population is exposed to indoor PM_{2.5} of outdoor-origin on average. Equation 3.6, enables us to obtain indoor PM_{2.5} of outdoor-origin concentration levels across different building segments in each grid cell; however, to calculate the average indoor concentration PM_{2.5} of outdoor-origin that is expected for the population to be exposed to, a population-weighted average of the pollution across different residential segments is needed. For this purpose, a new parameter, called ϕ , representing the proportion of the population living in each residential segment was used. The national values of ϕ estimated based on data gathered from the U.S. Census Bureau (2024) are shown in Table 3.1.

$$C_{r,g} = F_{r,g} \cdot C_{out} \quad (3.6)$$

Table 3.1: National average values for ϕ showing the proportion of the population living in each residential segment.

Building Type	Construction Decade (Vintage)	National Average ϕ
Single-Family Homes	Pre 1940	0.1
	Between 1940 - 1980	0.33
	Between 1980 - 2010	0.3
Multi-Family 2-4 Units	Pre 1940	0.01
	Between 1940 - 1980	0.03
	Between 1980 - 2010	0.03
Multi-Family 5+ Units	Pre 1940	0.02
	Between 1940 - 1980	0.06
	Between 1980 - 2010	0.05
Mobile Homes	Pre 1940	0.01
	Between 1940 - 1980	0.03
	Between 1980 - 2010	0.02

Utilizing ϕ , the mean C_r for each grid cell can be calculated as shown in Equation 3.7, where $\bar{C}_g$ is the mean indoor concentration across all residential buildings in grid cell g , and ϕ_r is the percentage of the population living in residential category r . The process explained is repeated for all grid cells.

$$\bar{C}_g = \sum_r C_{r,g} \cdot \phi_r \quad (3.7)$$

3.2.3.2 Intervention Scenario

Interventions aimed at improving building air tightness entail changes in the building's air change rate due to infiltration. In each intervention scenario, a modification in the air change rate of the targeted segment is applied to the model. This adjustment is applied by changing the ACH_{50} as shown in Equation 3.4 by a new value targeted by the intervention scenario and obtaining $\lambda'_{r,g}$. Then $\lambda'_{r,g}$ replaces $\lambda_{r,g}$ in all the mentioned equations and the same process is repeated. This adjustment initially alters the infiltration factor of the

targeted sector, consequently influencing the indoor concentration of that segment and impacting the overall grid cells, as shown in Equation 3.8.

$$\bar{C}'_g = \sum_r C'_{r,g} \cdot \phi_r \quad (3.8)$$

Ultimately, any intervention affects the mean concentration levels of the grid cell. This modeling approach allows flexibility to analyze a wide spectrum of possible scenarios, as interventions can be integrated into the model, affecting different residential segments and varying from grid cell to grid cell.

Finally, the changes in indoor concentration for each grid cell can be calculated as Equation 3.9, which afterward is plugged into the C-R function explained in the next section (3.2.4) to estimate health outcomes of the intervention.

$$\Delta \bar{C}_g = \bar{C}'_g - \bar{C}_g \quad (3.9)$$

3.2.4 Health Impact

Health impacts of interventions are due to changes in the indoor level of outdoor-origin PM_{2.5}, as explained in Section 3.2.3. These impacts on human health are quantified by using C-R functions.

In Section 2.4, a review of C-R functions was conducted. Traditional C-R functions were explained, along with their drawback for indoor applications. It was mentioned that the traditional C-R functions underestimate health impacts if changes in indoor pollution concentration are input to them directly, thus rendering them unsuitable and incorrect for indoor air pollution studies. Next, similar studies that tackled the same issue were briefly mentioned, noting their approaches to address this problem. Here, the modified C-R function, derived for the purposes of this particular study is explained in detail.

The exposure of an individual to PM_{2.5} is influenced by various factors (Bhoonah et al., 2023). For the purposes of this study, a simplified yet adequate representation of an individual's exposure can be expressed as the sum of the time spent in different micro-environments with varying PM_{2.5} levels. In this context, the major micro-environments in which Americans spend their time include outdoors, in vehicles, and indoors. However, there is significant variability among the types of indoor micro-environments individuals inhabit, with residences being a primary category alongside other indoor spaces. The total exposure of an individual can be expressed as Equation 3.10.

$$E = t_{\text{out}} \cdot C_{\text{out}} + t_v \cdot C_v + t_r \cdot C_r + t_{\text{other}} \cdot C_{\text{other}} \quad (3.10)$$

Where:

- C_v is the concentration of outdoor-origin PM_{2.5} inside vehicles ($\mu\text{g}/\text{m}^3$).
- C_r is the concentration of outdoor-origin PM_{2.5} inside residences ($\mu\text{g}/\text{m}^3$).
- C_{other} is the concentration of outdoor-origin PM_{2.5} inside other indoor environments ($\mu\text{g}/\text{m}^3$).
- t_{out} is the fraction of daily time, on average, that Americans spend outdoors (unitless).
- t_v is the fraction of daily time, on average, that Americans spend inside vehicles (unitless).
- t_r is the fraction of daily time, on average, that Americans spend in residences (unitless).
- t_{other} is the fraction of daily time, on average, that Americans spend in other indoor environments (unitless).

The concentration levels in each micro-environment can be calculated using Equation 3.11, where j is the index of a given environment and F_j is the infiltration factor of that environment.

$$C_j = F_j \cdot C_{\text{out}} \quad (3.11)$$

As evident in Equations 3.10 and 3.11, the exposure levels are proportional to the outdoor concentration levels. Therefore, a coefficient to adjust the traditional C-R functions for this study's specific requirements can be easily calculated. The methodology proposed here is consistent with similar works in the literature (Azimi & Stephens, 2020; Sparks et al., 2024; D. Zhao et al., 2015). Equations 3.12 through 3.20 show the process of calculating the adjustment coefficient, referred to as Ψ .

$$\frac{E'}{E} = \frac{C'_{\text{out}}}{C_{\text{out}}} \quad (3.12)$$

Where:

- E' is the exposure after intervention ($\mu g/m^3$).
- C'_{out} is the equivalent outdoor concentration that leads to similar exposure after intervention ($\mu g/m^3$).

$$C'_{out} = C_{out} \cdot \frac{E'}{E} \quad (3.13)$$

$$\Delta C_{out} = C'_{out} - C_{out} \quad (3.14)$$

$$\Delta E = E' - E \quad (3.15)$$

$$\Delta C_{out} = C_{out} \cdot \left(1 - \frac{E'}{E}\right) = C_{out} \cdot \frac{\Delta E}{E} \quad (3.16)$$

Since the interventions only impact the indoor concentration of residences in this study and all other terms in the exposure function remain the same, ΔE can be written as Equation 3.17.

$$\Delta E = t_r \cdot \Delta C_r \quad (3.17)$$

$$\begin{aligned} \Delta C_{out} &= \frac{\Delta E}{t_{out} \cdot C_{out} + t_v \cdot C_v + t_r \cdot C_r + t_{other} \cdot C_{other}} \cdot C_{out} \\ &= \frac{\Delta E}{C_{out} \cdot (t_{out} + t_v \cdot F_v + t_r \cdot F_r + t_{other} \cdot F_{other})} \cdot C_{out} \end{aligned} \quad (3.18)$$

$$\begin{aligned} &= \frac{t_r}{t_{out} + t_v \cdot F_v + t_r \cdot F_r + t_{other} \cdot F_{other}} \cdot \Delta C_r \\ \Psi &= \frac{t_r}{t_{out} + t_v \cdot F_v + t_r \cdot F_r + t_{other} \cdot F_{other}} \end{aligned} \quad (3.19)$$

$$\Delta C_{out} = \Psi \cdot \Delta C_r \quad (3.20)$$

Therefore, the equivalent outdoor changes resulting from a change equal to ΔC_r in indoor concentration of outdoor-origin PM_{2.5} inside residences can be calculated using Equation 3.20. Then, the log-linear H-I function with a modified C-R function is rewritten as Equation 3.21, which gives the change in risk of mortality incidence.

$$\Delta Y = Y_0 \cdot (1 - \exp^{-\beta \cdot \Psi \cdot \Delta C_r}) \quad (3.21)$$

The Ψ value calculated in this study is equal to 1.248, the parameters used for calculating Ψ are summarized in Table 3.2.

Now using the modified C-R function explained, the reduced concentration levels calculated using Equation 3.9, are plugged into Equation 3.21 and the change in mortality risk is obtained. Finally, the total avoided premature mortality could be calculated as Equation 2.7 as similar to explained in the Section 2.4.

Table 3.2: Values for time fraction spent in micro-environments, and infiltration factor for each micro-environment used to calculate Ψ

Parameter	Value	Source	Parameter	Value	Source
t_{out}	0.076	(Klepeis et al., 2001)	F_{out}	1	-
t_v	0.055	(Klepeis et al., 2001)	F_v	0.6	(Rodes et al., 1998)
t_r	0.687	(Klepeis et al., 2001)	F_r^a	0.55	(Reyna et al., 2022)
t_{other}	0.182	(Klepeis et al., 2001)	F_{other}	0.35	(Fisk & Chan, 2017b)

^aNational average calculated based on ResStock.

3.2.5 Economic Evaluation

3.2.5.1 Benefits

To estimate the benefits of intervention based on the principles explained in Section 2.5, the mortality incidence rate reduction and avoided premature mortality caused by intervention can then be used together with VSL for calculating the economic benefits of intervention in each grid cell. The benefits of any grid cell (B_g) and the national benefits (TB) can be estimated using Equations 3.22 and 3.23, respectively.

$$B_g = \Delta Mort_g \cdot VSL \quad (3.22)$$

$$TB = \sum_g B_g \quad (3.23)$$

Benefits per capita for each grid or whole nation are derived by dividing the population benefits by the population of a given grid or the nation.

3.2.5.2 Costs

Cost data have been sourced from the LBNL study called “The Cost of Decarbonization and Energy Upgrade Retrofits for US Homes” (Section 3.2.2.6). This information specifies the cost of improving houses per percentage point of leakage reduction. The percentage of leakage reduction required for each intervention can be calculated as Equation 3.24, and then the expected cost of upgrading a single house can be obtained by using Equation 3.25. Finally, the total cost of the intervention at both grid and national levels can be estimated using Equations 3.26 and 3.27, respectively.

$$\%R\lambda_{r,g} = \frac{\lambda_{r,g} - \lambda'_{r,g}}{\lambda_{r,g}} \quad (3.24)$$

$$CH_{r,g} = P_{\%R\lambda} \cdot A_{r,g} \quad (3.25)$$

$$CG_g = Pop_g \cdot \sum_r \frac{CH_{r,g}}{O_{r,g}} \cdot \phi_r \quad (3.26)$$

$$TC = \sum_g CG_g \quad (3.27)$$

Where:

- $\%R\lambda_{r,g}$ is the percentage of building leakage reduction required under the intervention scenario.
- $CH_{r,g}$ is the average cost of upgrading a house from segment r in grid g (USD).

- $P_{\%R\lambda}$ is the price of upgrading for $\%R\lambda$ of leakage reduction (USD per sqft).
- $A_{r,g}$ is the average size of a house in segment r in grid g (sqft).
- CG_g is the cost of intervention in grid g (USD).
- $O_{r,g}$ is the average occupancy of a house of segment r in grid g (person).

3.2.5.3 Net Benefits

Net benefits are a measure used to determine whether an intervention scenario economically generates more benefits than costs. The net benefit in each grid cell (NB_g) is calculated using Equation 3.28, while nationwide net benefits (TNB) are determined using Equation 3.29. The net benefits per capita can be obtained by dividing population net benefits by the population.

$$NB_g = B_g - C_g \quad (3.28)$$

$$TNB = TB - TC \quad (3.29)$$

It is important to note that while the net benefits may be negative in some grid cells, the nationwide net benefits can still be positive. This occurrence provides decision-makers with critical insights, enabling informed decision-making across different scales. The aforementioned will be discussed more in Chapter 4.

3.2.6 Uncertainty Modeling

As mentioned in Chapter 2, many sources of uncertainty impact the model's results. To account for these uncertainties, and to calculate the 95% confidence interval, Monte Carlo Simulation (MCS) with 1000 iterations has been used. In each MCS iteration, the uncertain parameters are sampled from their respective distributions to account for the model's uncertainties. These distributions for the parameters were either identified in the literature or developed by this study. The choice of 1000 iterations has been made due to computation time and output file size limitations.

Parameters such as the penetration factor, deposition rate, risk estimate (β), and the Value of a Statistical Life (VSL) were reviewed in the literature, and corresponding distributions were identified. More details on the uncertainty and distributions of these parameters were discussed in Chapter 2. Given the substantial variation found in the literature, distributions were selected based on common approaches cited in the literature or based on the judgment of the author of this study, as shown in Table 3.3.

For parameters like ACH_{50} , floor area, and occupancy, distributions for each segment within every grid cell were created using a stochastic sampling method from ResStock, as detailed in Section 3.2.2.2.3. Examples of these distributions are illustrated in Figures 3.10, 3.11, and 3.12 respectively.

Table 3.3: Uncertain parameters distributions from the literature

Parameter	Distribution	Parameters	Source	Figure
Penetration Factor	Truncated Normal	min = 0 max = 1 $\mu = 0.72$ $\sigma = 0.21$	(Williams et al., 2003)	A.3
Particle Deposition	Truncated Normal	min = 0 $\mu = 0.39$ $\sigma = 0.08$	(Fisk & Chan, 2017b)	A.4
β	Normal	$\mu = 0.0058$ $\sigma = 0.001$	(Krewski et al., 2009)	A.5
VSL	Weibul	$\mu = 8,705,114$ (2015 USD) shape = 1.51 scale = 9,648,168	(EPA, 2023)	A.6

To model the uncertainty associated with cost estimation, median (Equation 3.1), minimum (Equation 3.2), and maximum (Equation 3.3) values for each leakage reduction level that is calculated using Equation 3.24 are derived from the regressions obtained in Section 3.2.2.6. Given the available data, a triangular distribution was deemed the most suitable approach. However, the available data does not provide the mode necessary to parameterize a triangular distribution. Assuming that the median values are approximately located in the middle of the ranges, a symmetrical triangular distribution is assumed. Consequently, the parameters of a triangular distribution are established, where a the minimum is $P_{\%RA}^{min}$, b the maximum is $P_{\%RA}^{max}$ and c , the mode, is determined for symmetrical distributions using Equation 3.30.

$$c = \frac{a + b}{2} \quad (3.30)$$

Then the price parameter for a given $\%R\lambda$ is sampled from a Triangular distribution as outlined in Equation 3.31

$$Triangular(a = P_{\%R\lambda}^{min}, b = P_{\%R\lambda}^{max}, c = \frac{P_{\%R\lambda}^{min} + P_{\%R\lambda}^{max}}{2}) \quad (3.31)$$

In the results section (4.2.2), a thorough uncertainty analysis is conducted by isolating uncertain parameters to generate insights.

Chapter 4

Results & Discussion

This section presents the results from the application of the integrated model developed in Chapter 3 to evaluate the health and economic impacts of improving the airtightness of United States single-family homes. It explores the national and spatial impacts of various intervention scenarios, including reductions in indoor $\text{PM}_{2.5}$ from outdoor sources, changes in mortality risk, total premature mortality avoided, health benefits, costs, and the net benefits of intervention measures. The results are presented for a hypothetical year referred to as the intervention year, which reflects the average characteristics of the period from 1980 to 2010. Also, all monetary values are reported in 2020 United States Dollars.

To ensure a thorough evaluation, as discussed in the research scope (Section 1.2) this section initially assesses the potential health impacts and the costs and benefits of upgrading single-family homes to meet IECC 2018 code levels. Then, sensitivity analysis is conducted. First, a sensitivity analysis on alternative targets for leakage reduction levels is conducted to enhance the robustness of the analysis and mitigate the risk of overestimation. Second, the sensitivity of the model to uncertain input variables is evaluated to understand each variable's impact on the uncertainty of the results.

4.1 IECC Targets

IECC 2018, which is equivalent to IECC 2012 and IECC 2015, has been selected as the target for this analysis rather than IECC 2021. This choice is based on the time frame of this study, which concentrates on the scenario at the start of the century, and the residential stock data which includes buildings from prior to the year 2020.

The mandated airtightness levels specified in IECC 2018, as detailed in Section 2.1.1, require climate zones one and two to achieve an airtightness of 5 ACH₅₀, and climate zones three through eight to achieve 3 ACH₅₀. Consequently, the intervention scenario examined in this study involves improving the airtightness of single-family homes to meet the recommended ACH₅₀ levels for their respective climate zones, as per IECC 2018.

To enhance the accuracy and depth of the insights derived from the analysis, single-family homes were categorized into three segments based on their year of construction. This segmentation, detailed in Section 3.2.2.2, divides homes into Vintage 1 (V1) for buildings constructed before 1940, Vintage 2 (V2) for those built between 1940 and 1980, and Vintage 3 (V3) for buildings constructed after 1980. Four intervention scenarios were subsequently defined, as outlined in Table 4.1, to facilitate a comprehensive evaluation by targeting specific building segments as well as the entire single-family home segment.

Table 4.1: IECC 2018 Based Targets, Intervention Scenarios for Single-Family Homes

Scenario	Description
IECC V1	Intervention in Single-Family homes constructed pre 1940 to comply with IECC2018 indicated ACH ₅₀ values.
IECC V2	Intervention in Single-Family homes constructed between 1940-1980 to comply with IECC2018 indicated ACH ₅₀ values.
IECC V3	Intervention in Single-Family homes constructed post 1980 to comply with IECC2018 indicated ACH ₅₀ values.
IECC ALL	Intervention in all Single-Family homes to comply with IECC2018 indicated ACH ₅₀ values.

For each scenario, following the methodology outlined in Chapter 3, the reduction in daily average indoor PM_{2.5} levels of outdoor-origin, compared to the baseline state, is calculated. Subsequently, the decrease in mortality risk and the number of premature deaths avoided are determined. Finally, the economic benefits and costs of the intervention are estimated. Here the national and spatial results of these simulations are described in detail.

4.1.1 National Average Results

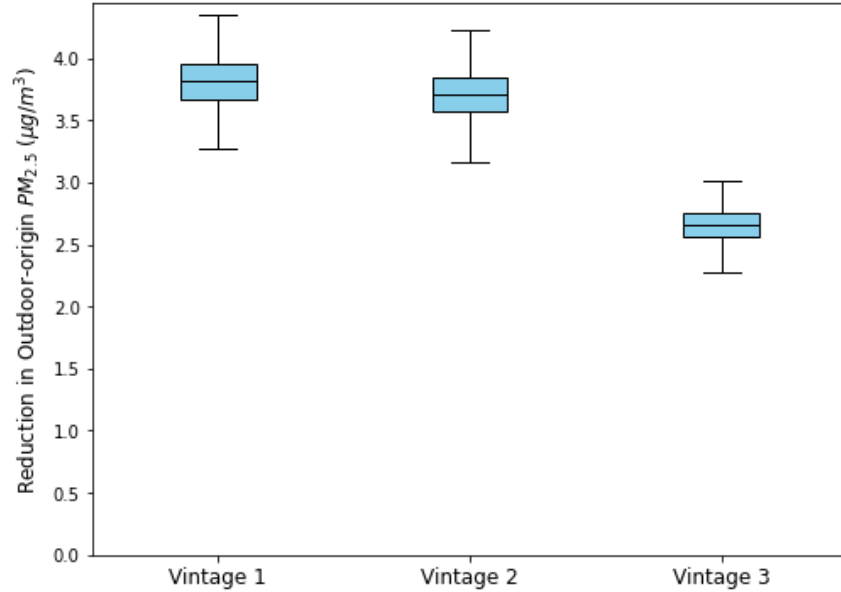


Figure 4.1: Displays the value and uncertainty of the reduction in daily mean of $PM_{2.5}$ from outdoor sources within each vintage as a result of the intervention to comply with IECC 2018 standards.

The results of the simulations indicate that interventions impact different age groups of buildings differently, with older buildings, typically less airtight, experiencing the most significant impact. Figure 4.1 illustrates the expected impact of compliance with IECC 2018 on reducing indoor $PM_{2.5}$ levels originating from outdoor sources. Vintage 1 buildings show the most substantial reduction, with a decrease of $3.81\mu g/m^3$ in daily mean indoor $PM_{2.5}$, closely followed by Vintage 2 at $3.7\mu g/m^3$. On the other hand, Vintage 3, which includes the newest single-family homes, experience the smallest improvement in air quality, with a reduction of only $2.65\mu g/m^3$. The 95% confidence intervals displayed in the figure reflect the uncertainties in the variables used to calculate the infiltration factor, which then influences the indoor levels of outdoor-origin $PM_{2.5}$. These uncertain variables were thoroughly explained in Section 3.2.6.

Table 4.2 provides a summary of the national average health and economic impacts of complying with the IECC 2018 recommended ACH_{50} levels across all scenarios listed in Table 4.1. The data in Table 4.2 highlight not only the significant benefits but also the

Table 4.2: IECC Scenario Analysis: Annual Benefits and Costs in 2020 USD

Scenario	Avoided Premature Mortality CI:(95%)	Benefits (Billion \$) CI:(95%)	Costs (Billion \$) CI:(95%)	Net Benefits (Billion \$) CI:(95%)
IECC V1	7,104 (4,655, 9,832)	55 (7, 193)	14.5 (13.9, 15.1)	41 (-8, 178)
IECC V2	22,709 (15,426, 30,820)	178 (19, 641)	44 (42, 46)	133 (-24, 596)
IECC V3	14,885 (9,509, 20,054)	124 (16, 371)	46 (44, 48)	78 (-31, 325)
IECC ALL	44,611 (29,831, 58,905)	356 (45, 1,173)	105 (102, 107)	251 (-62, 1,067)

considerable uncertainty associated with reductions in premature mortality due to outdoor PM_{2.5} for all intervention scenarios. This uncertainty is further explored in section 4.2.2. Enhancing the airtightness of single-family homes markedly decreases health issues associated with the infiltration of outdoor PM_{2.5}. Specifically, if all single-family homes, which constitute 73% of the total residential stock, were to comply with the IECC 2018 mandates, it is estimated that annually 44,611 (29,831, 58,905) lives could be saved, yielding health benefits valued at \$356 (\$45, \$1,173) billion. The cost of these interventions is projected to be \$105 (\$102, \$107) billion, resulting in net health benefits of \$251 (-\$62, \$1,067) billion in the intervening year. The net benefits yielded from improving all vintages are the largest and ideally the preferred approach from a cost-benefit perspective. These findings underscore the considerable impact that improving the airtightness of single-family homes can have on human health and highlight the importance for policymakers to consider air pollution-related health impacts when formulating building standards policies.

Further analysis of the results reveals interesting insights, first examining the avoided premature mortality and benefits, and then analyzing the costs and net benefits. While Figures 4.2 and 4.4 show that the overall share of benefits for improving buildings in Vintage 1 (\$55 billion and 7,104 lives saved) is smaller than both Vintage 2 (\$178 billion and 22,709 lives saved) and Vintage 3 (\$124 billion and 14,885 lives saved), Figures 4.3 and 4.5 show that improving buildings in Vintage 1 are more impactful than Vintage 2 and 3 on a per-resident basis.

For instance, if a goal were to maximize health benefits, ignoring costs, by targeting a

limited number of buildings, focusing on Vintage 1 buildings would be most advantageous. Vintage 1 buildings yield \$3,066 in annual benefits per resident and reduce annual mortality risk by 39 per 100,000. In comparison, Vintage 2 buildings offer \$2,978 in annual benefits with a annual mortality risk reduction of 38 per 100,000, and Vintage 3 buildings provide \$2,285 in annual benefits with a annual mortality risk reduction of 27 per 100,000.

This can be explained by the fact that improving Vintage 1 buildings results in the most significant air quality improvement regarding outdoor-origin $PM_{2.5}$. Thus, individuals living in these buildings experience more health benefits. However, the relatively small proportion of Vintage 1 buildings within the total residential stock, only 10%, compared to 33% for Vintage 2 and 30% for Vintage 3, means that the overall projected benefits of enhancing the Vintage 1 segment are smaller than those for the other two.

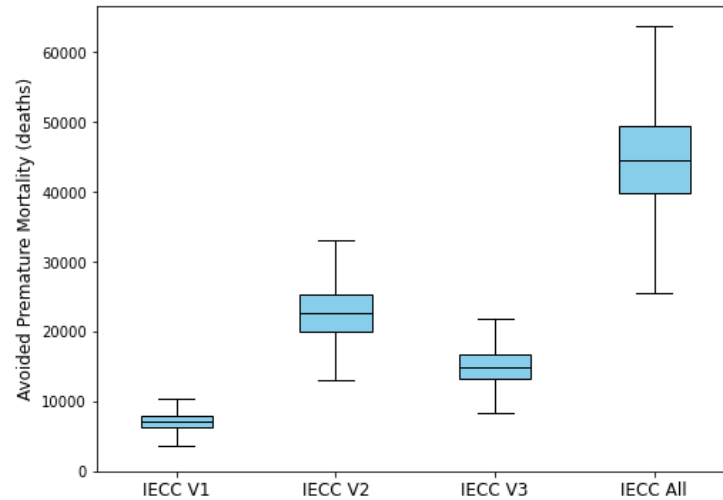


Figure 4.2: Illustrates the value and uncertainty of the annual averted premature mortality within each intervention scenario resulting from single-family homes complying with IECC 2018.

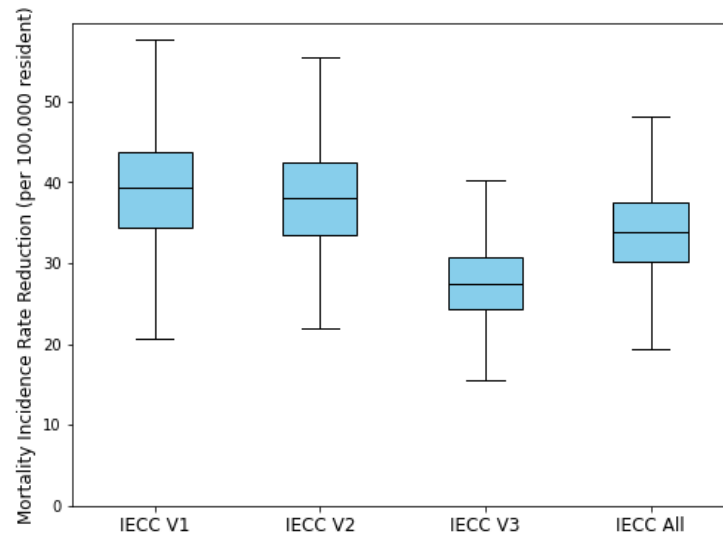


Figure 4.3: Illustrates the value and uncertainty of the reduction in the annual mortality incidence rate per 100,000 residents of single-family homes within each intervention scenario as a result of compliance with IECC 2018.

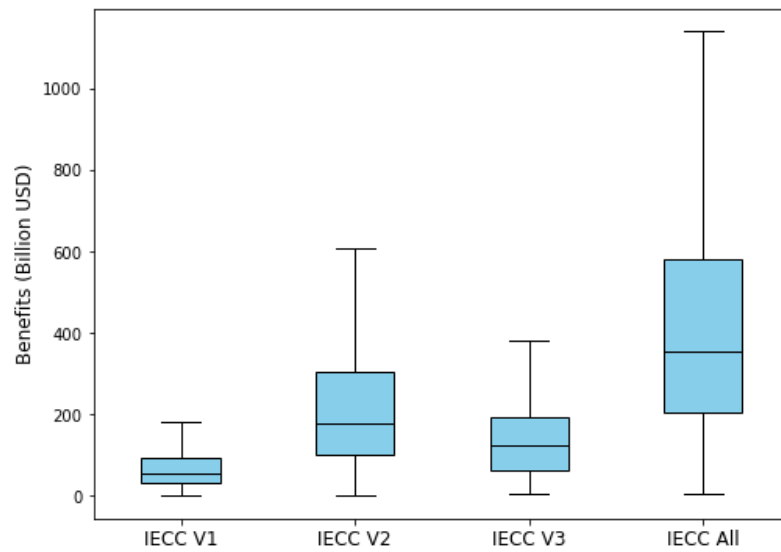


Figure 4.4: Illustrates the value and uncertainty of the annual total benefits within each intervention scenario resulting from single-family homes complying with IECC 2018.

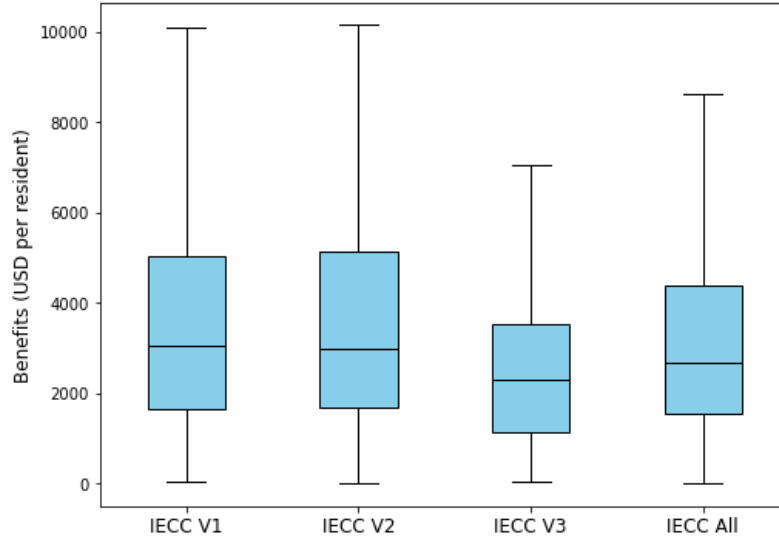


Figure 4.5: Illustrates the value and uncertainty of annual benefits per-resident of single-family homes within each intervention scenario as a result of compliance with IECC 2018.

Overall, the results show that the total national benefits significantly outweigh the costs, amounting to almost three times in value. The intervention costs across all buildings are estimated at \$105 billion, with Vintage 1, 2, and 3 contributing \$15 billion, \$44 billion, and \$46 billion, respectively (Figure 4.6). The cost of improving a house within each vintage is \$1,686 for Vintage 1, \$1,568 for Vintage 2, and \$1,860 for Vintage 3 (Figure 4.7). As a result, the total net benefits nationally in the intervention year is \$251 billion, with contributions of \$41 billion from Vintage 1, \$133 billion from Vintage 2, and \$78 billion from Vintage 3 (Figure 4.8). The net benefits per residence in the intervention year are \$2,263, \$2,239, and \$1,439 for Vintage 1, 2, and 3, respectively (Figure 4.9).

However, net benefits are subject to uncertainties introduced by the many uncertain parameters described in Section 3.2.6. This leads to a very broad range of national net benefits, with the 95% confidence interval ranging from -\$62 billion to \$1067 billion. When interpreting the results, this uncertainty should be accounted for. In Section 4.2.2, the uncertainty of the results is explored further.

Results generally suggest that interventions in Vintage 1 and Vintage 2 buildings are more cost-effective to pursue considering a limited budget, as improvements in these vintages offer greater benefits per dollar spent. The benefit-to-cost ratios are 3.79, 4.05, and 3.39 for Vintage 1, 2, and 3, respectively. However, there is considerable spatial variability

across the United States that should be taken into account when designing policies. Section 4.1.2 further discusses these spatial variabilities.

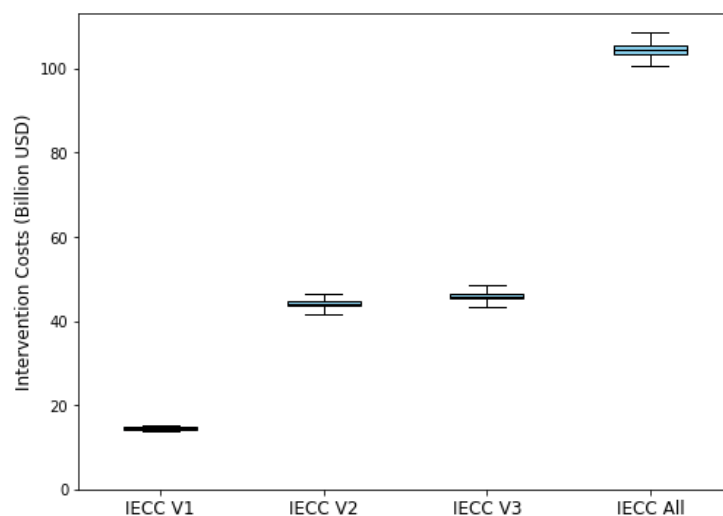


Figure 4.6: Illustrates the value and uncertainty of the total intervention costs within each intervention scenario resulting from single-family homes complying with IECC 2018.

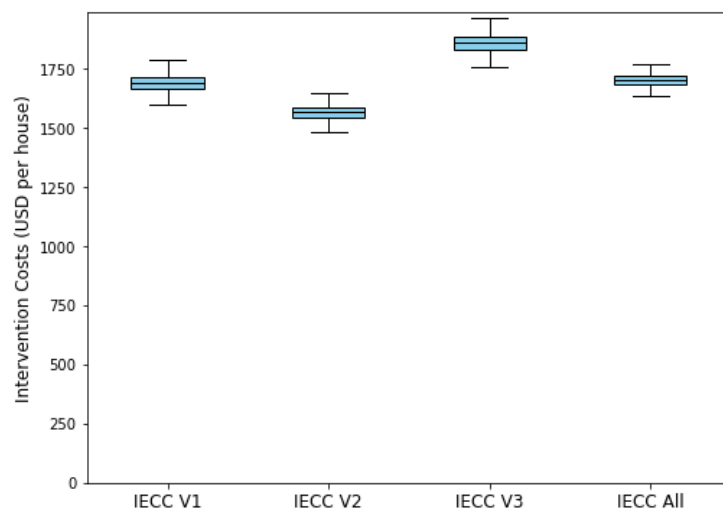


Figure 4.7: Illustrates the value and uncertainty of intervention costs per-house of single-family homes within each intervention scenario as a result of compliance with IECC 2018.

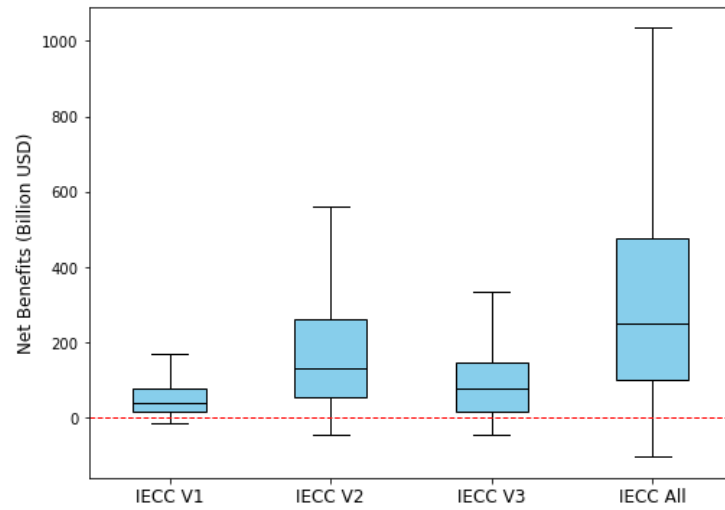


Figure 4.8: Illustrates the value and uncertainty of the total intervention year net benefits within each intervention scenario resulting from single-family homes complying with IECC 2018.

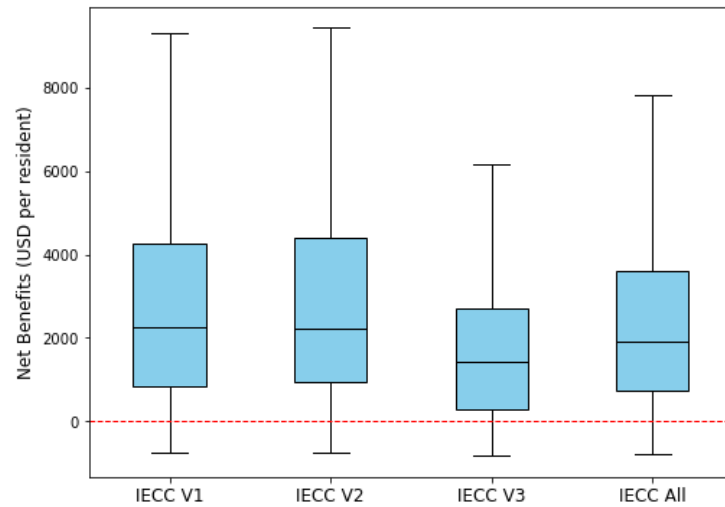


Figure 4.9: Illustrates the value and uncertainty of the intervention year net benefits per-resident of single-family homes within each intervention scenario as a result of compliance with IECC 2018.

4.1.2 Spatial Results

While Table 4.2 offers a national overview of the impacts of enhancing airtightness levels in single-family homes, simulations of different scenarios reveal substantial spatial variability across the United States.

The majority of avoided premature mortality and benefits from these interventions are predominantly concentrated in the eastern U.S. and in densely populated urban centers. Figure 4.10 shows the spatial distribution of impacts on the mortality incidence rate per 100,000 people from the “IECC ALL” intervention scenario, while Figure 4.11 illustrates the spatial distribution of the benefits per-resident. Starting from the East Coast, the largest benefits are observed near major urban centers such as New York and Chicago. As one moves north to states like Maine or south to Florida, the benefits decrease. Continuing westward, passing through the central United States and approaching the West Coast, the benefits are the lowest. However, near the western coastline, in larger urban centers such as Seattle and Los Angeles, benefits start to increase once again.

The skew of benefits toward the eastern states can be attributed to the higher air pollution levels in this region, as shown in Figure 4.12, leading to greater reductions in indoor $\text{PM}_{2.5}$ (Figure 4.13) as a result of the interventions, causing greater benefits.

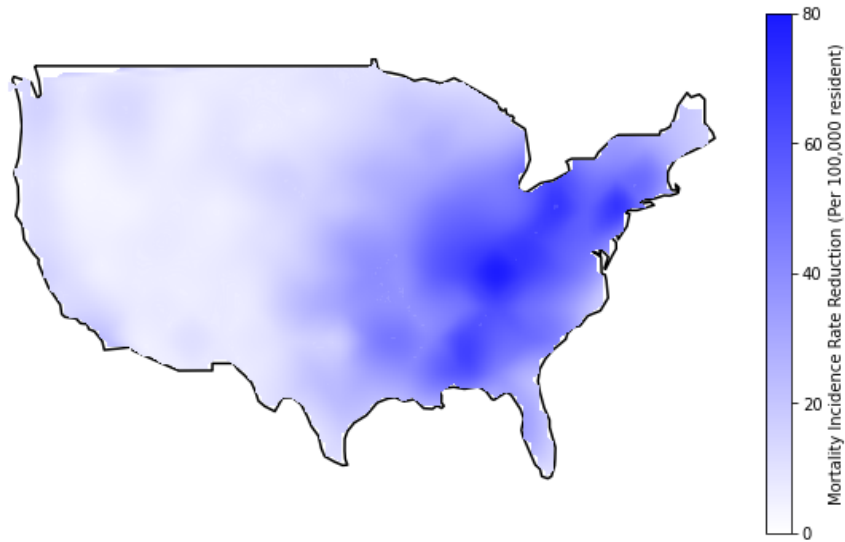


Figure 4.10: Illustrates the spatial distribution of the annual reduction in mortality incidence rate per 100,000 residents of single-family homes resulting from compliance with IECC 2018 across all single-family homes.

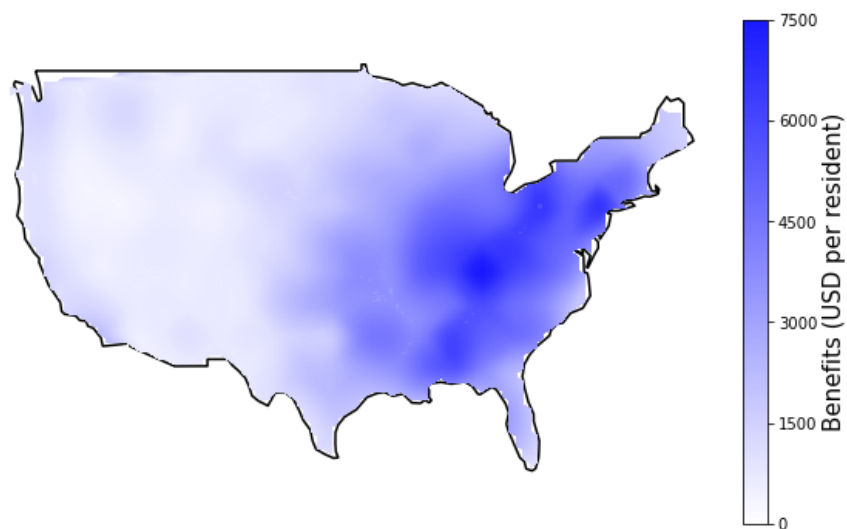


Figure 4.11: Illustrates the spatial distribution of the annual benefits per-resident of single-family homes resulting from compliance with IECC 2018 across all single-family homes.

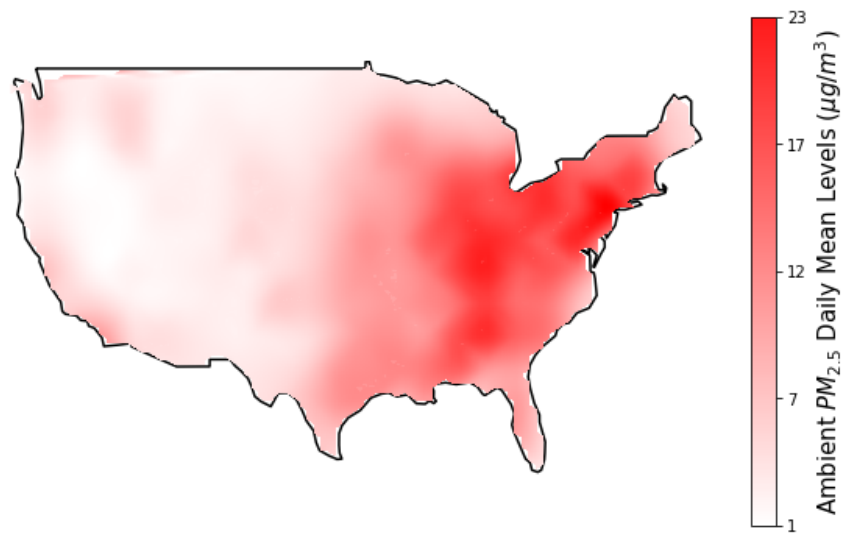


Figure 4.12: Illustrates the spatial distribution of daily average outdoor $PM_{2.5}$ concentration levels for the start of the century period (1980 to 2010).

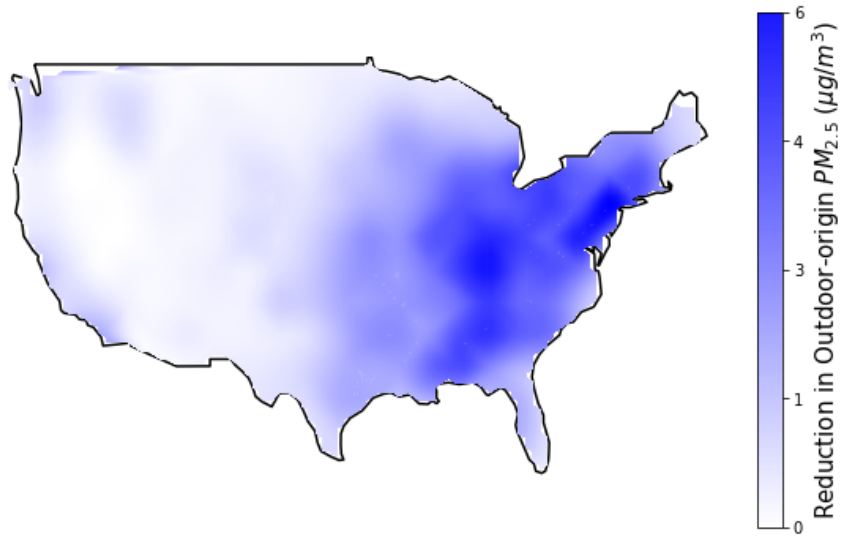


Figure 4.13: Illustrates the spatial distribution of reduced daily mean level of outdoor-origin $PM_{2.5}$ inside single-family homes as the result of complying by IECC 2018.

Figure 4.14 illustrates the leakage reduction required for single-family homes to comply with IECC 2018 standards. The reduction requirement is almost evenly distributed across the country, with slightly lower reduction requirements in the South and Southwest. This even distribution has led to more uniformly distributed costs nationwide, as indicated in Figure 4.15, with the lowest values observed in the South and Southwest.

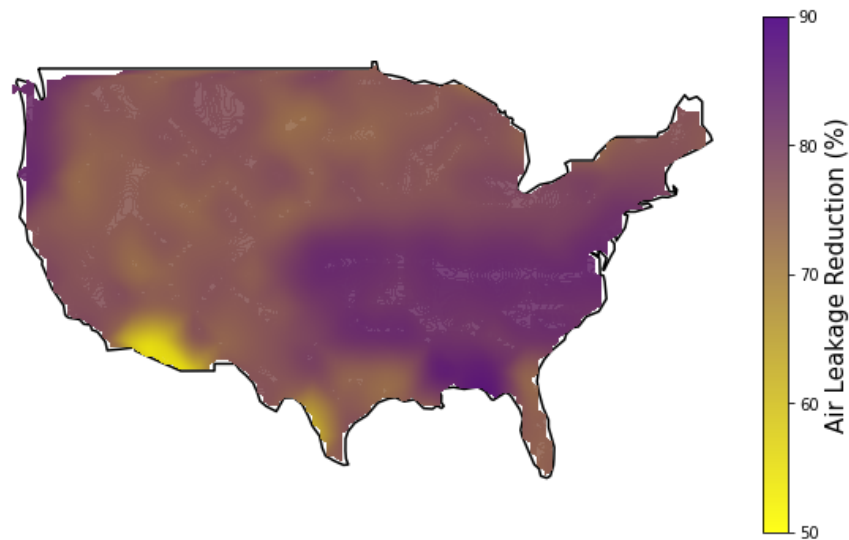


Figure 4.14: Illustrates the spatial distribution of the leakage reduction required for single-family homes to bridge the gap between the current stock and the standards recommended by IECC 2018.

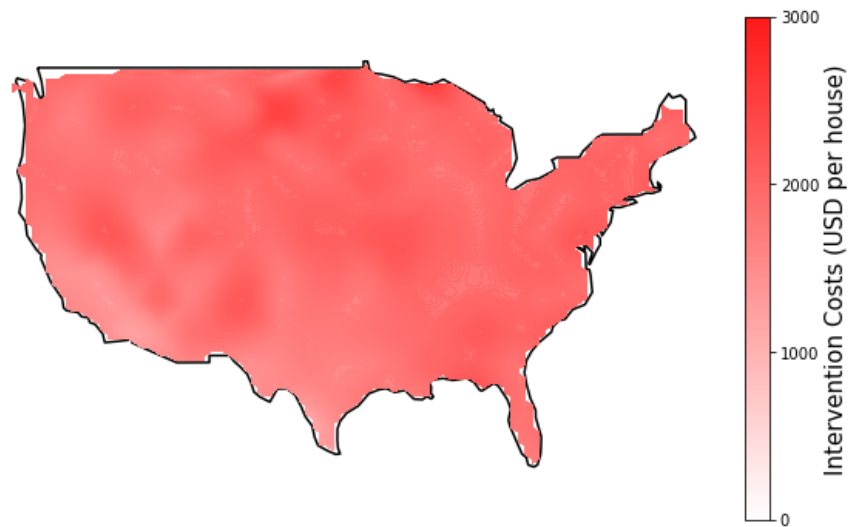


Figure 4.15: Illustrates the spatial distribution of the intervention costs per-resident of single-family homes resulting from compliance with IECC 2018 across all single-family homes.

The significant benefits realized in the eastern U.S., as shown in Figure 4.11, along with the evenly distributed costs, create a clear divide in net benefits between the western and eastern U.S., as illustrated in Figure 4.16. The results indicate that net benefits are largest in the eastern U.S., decreasing westward, turning negative, and then slightly rising above zero near the coastline and major population hubs. However, due to the significant magnitude of benefits in the eastern U.S., the overall net benefits for the United States remain positive.

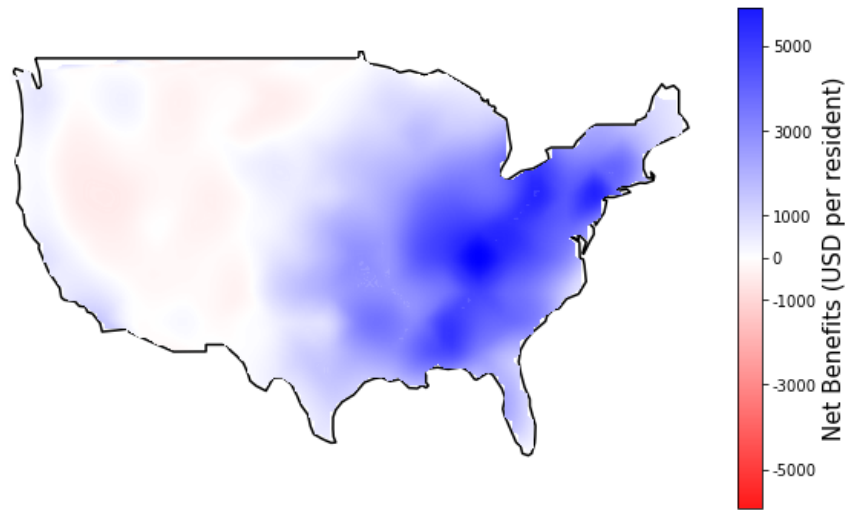


Figure 4.16: Illustrates the spatial distribution of the intervention year net benefits per-resident of single-family homes resulting from compliance with IECC 2018 across all single-family homes.

However, when examining each vintage separately, Vintage 1 shows that even in the western U.S., the net benefits are mostly positive (Figure 4.17). This could be attributed to Vintage 1 buildings having the most significant air leakage reduction and the most substantial impact on reducing indoor $\text{PM}_{2.5}$ of outdoor-origin. In contrast, for Vintage 3, which represents the most airtight segment, net benefits are mostly negative in the western U.S. (Figure 4.18). This is due to the limited impact that improving airtightness has on reducing outdoor-origin $\text{PM}_{2.5}$ in these buildings.

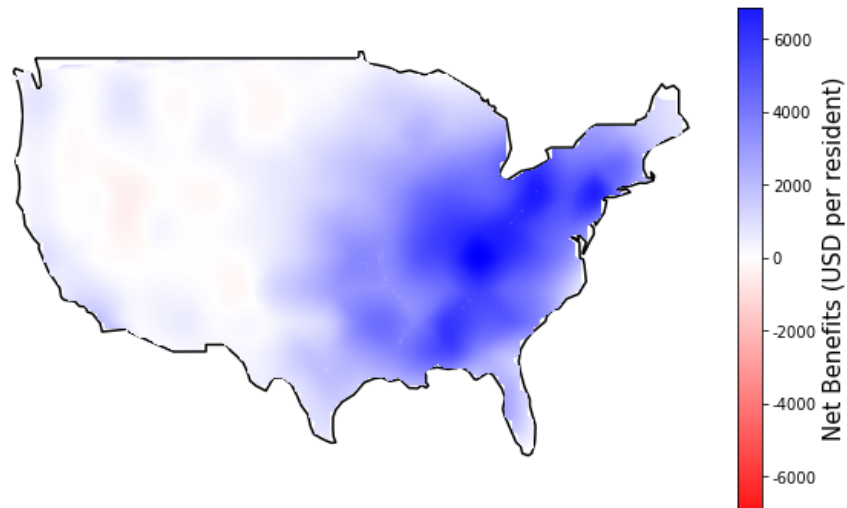


Figure 4.17: Illustrates the spatial distribution of the intervention year net benefits per-resident of single-family homes resulting from compliance with IECC 2018 across Vintage 1 single-family homes.

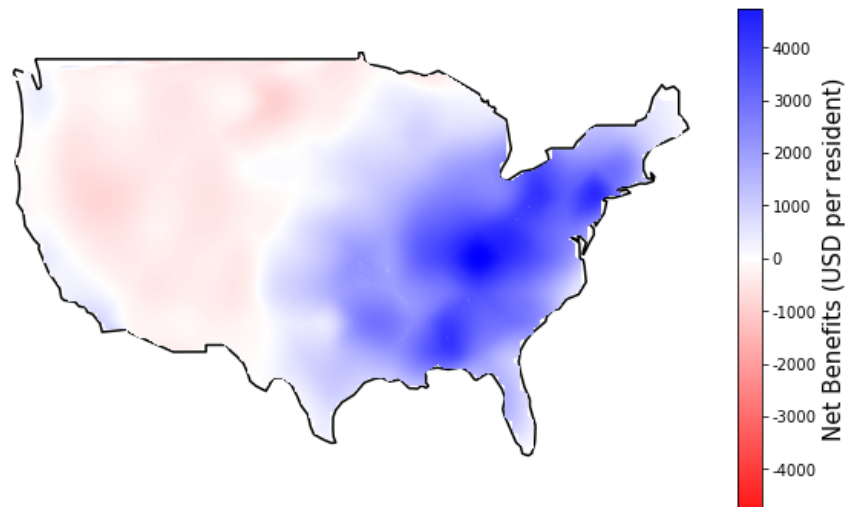


Figure 4.18: Illustrates the spatial distribution of the intervention year net benefits per-resident of single-family homes resulting from compliance with IECC 2018 across Vintage 3 single-family homes.

4.2 Sensitivity Analysis

This section is dedicated to simulating additional scenarios for the sensitivity analysis of the model, aiming to create a more comprehensive picture of the results. It first assesses the impacts of different leakage reduction levels, and then examines the sensitivity of the outputs to the uncertainty of the inputs.

4.2.1 Sensitivity Analysis of Air Leakage Reduction Levels

The previous section demonstrated the impacts of upgrading single-family homes' airtightness to meet IECC 2018 standards. Under that scenario, an average leakage reduction of approximately 79% was required to comply with the code, resulting in significant potential impacts, with the upper bound of the 95% confidence interval reaching \$1,067 billion in annual national net benefits. However, since most airtightness improvement efforts in practice are part of energy efficiency retrofits, it is crucial to assess the actual impact of these retrofits on airtightness. Sherman and Dickerhoff (1998) demonstrates that weatherization retrofits lead to an average infiltration reduction of 26%. Similarly, Zhao (2019) reports that leakage reduction, expressed as ACH_{50} , decreased by $16\% \pm 17$ as a result of energy efficiency retrofits. These findings highlight a significant gap between the leakage reductions typically achieved in practice and those required to meet the IECC 2018 targets.

Clearly, if the analysis is limited only to IECC targets, it considers merely the best-case scenario and neglects other practical possibilities, making the results susceptible to over-estimation. Therefore, alternative air leakage reduction scenarios beyond simply meeting code levels, from a lower reduction level of 20% up to 60%, are explored to ensure a more robust and realistic analysis. Table 4.3 outlines the scenarios defined for the sensitivity analysis of air leakage reduction. Furthermore, Table 4.4 provides a summary of the results.

Table 4.3: Contains the definition of sensitivity analysis scenarios on air leakage reduction levels for single-family homes.

Scenario	Description
R20	Intervention in all Single-Family homes to reduce ACH ₅₀ by 20%
Energy Star (R25) ^a	Intervention in all Single-Family homes to reduce ACH ₅₀ by 25%
R40	Intervention in all Single-Family homes to reduce ACH ₅₀ by 40%
R60	Intervention in all Single-Family homes to reduce ACH ₅₀ by 60%
IECC 2018	Intervention in all Single-Family homes to comply with IECC2018 indicated ACH ₅₀ values.

^aBased on the Energy Star online calculator, which estimates energy savings from air sealing reduction retrofits, it is noted that a 25% reduction in infiltration can be achieved by sealing air leaks throughout the house. Key focus areas include leaks in the attic space, through the foundation, and around windows and doors (Energy Star, 2014).

As expected, different leakage reduction levels lead to significantly varied results. As shown in Figure 4.19, the reduction in indoor levels of outdoor-origin PM_{2.5} increases with higher leakage reduction levels, ranging from 0.39 $\mu\text{g}/\text{m}^3$ in scenario R20 to 3.3 $\mu\text{g}/\text{m}^3$ in scenario IECC ALL. This variation translates into notable differences in health and economic impacts. The increasing trend and the growing uncertainty associated with higher levels of leakage reduction are also evident in Figures 4.20 and 4.21.

Table 4.4: Sensitivity Scenario Analysis: Annual Benefits and Costs in 2020 Dollars

Scenario	Avoided Premature Mortality CI:(95%)	Benefits (Billion \$) CI:(95%)	Costs (Billion \$) CI:(95%)	Net Benefits (Billion \$) CI:(95%)
R20	5,325 (3,597, 7,041)	43 (5, 142)	48 (47, 49)	-5 (-43, 94)
Energy Star (R25)	6,868 (4,693, 9,353)	58 (6, 181)	53 (51, 54)	5 (-47, 128)
R40	12,832 (8,151, 16,974)	100 (10, 321)	67 (66, 69)	33 (-57, 254)
R60	24,026 (15,639, 32,697)	197 (25, 642)	87 (85, 89)	110 (-62, 553)
IECC ALL	44,611 (29,831, 58,905)	356 (45, 1,173)	105 (102, 107)	251 (-62, 1,067)

Avoided premature mortality and the benefits of improving building airtightness increase significantly from the R20 scenario to the IECC ALL scenario, escalating more than 8 times from 5,325 lives saved annually and \$43 billion in annual benefits to 44,611 lives saved and \$356 billion in benefits. However, the costs exhibit less variation, only doubling from \$48 billion to \$105 billion. The variations in costs and benefits and the disparity in the magnitude of their growth with increased leakage reduction levels lead to disproportionate net benefit growth compared to benefit growth among scenarios. The R20 scenario shows a negative median for net benefits of -\$5 billion, suggesting that intervention costs are likely to outweigh the benefits. However, this quickly changes with only a 5 percent increase in reduction to the R25 scenario, leading to positive net benefits of \$5 billion. This value escalates up to 50 times to \$251 billion in the IECC ALL scenario.

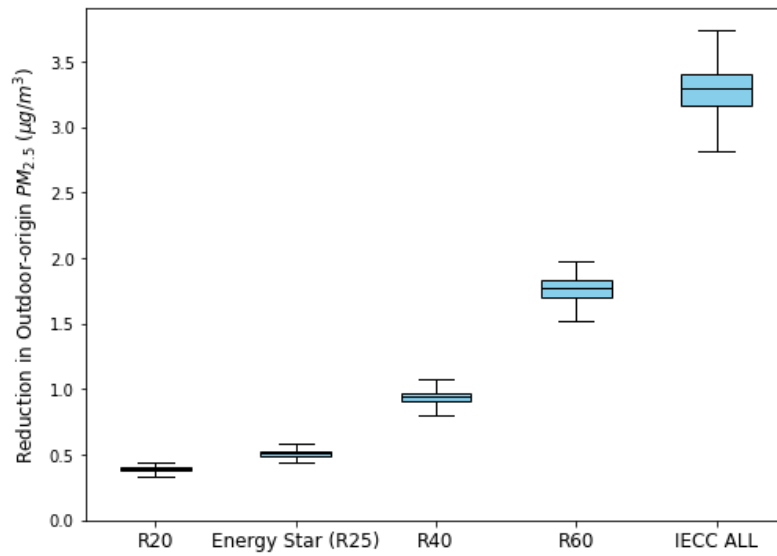


Figure 4.19: Displays the value and uncertainty of the reduction in indoor $PM_{2.5}$ daily mean from outdoor source as a result of single-family homes air leakage reduction under each sensitivity scenario.

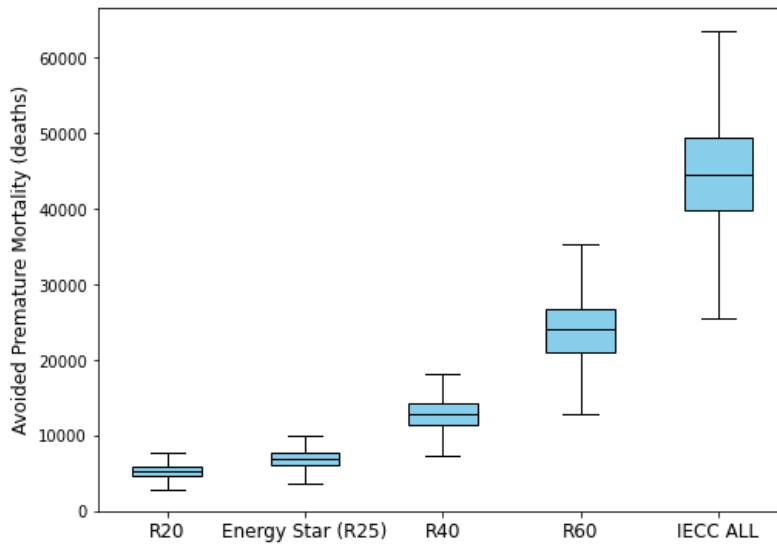


Figure 4.20: Illustrates the value and uncertainty of the annual total mortality avoided as a result of single-family homes air leakage reduction under each sensitivity scenario.

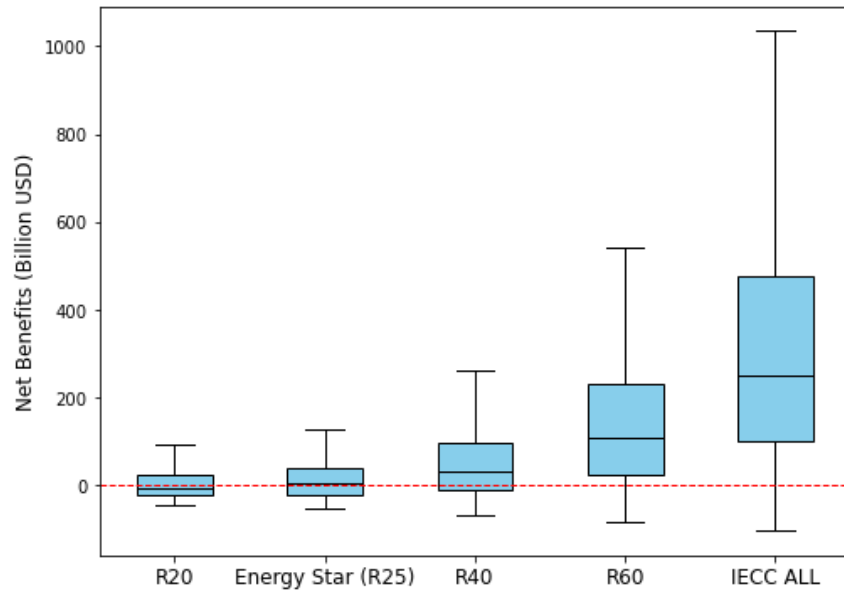


Figure 4.21: Illustrates the value and uncertainty of the intervention year total net benefits as a result of single-family homes air leakage reduction under each sensitivity scenario.

Spatial analysis of net benefits also provides insightful results. As depicted in Figure 4.16, the net benefits are most significant in the eastern U.S. and turn negative in the western U.S. up to the coastline. However, as the leakage reduction level decreases, the boundary of positive net benefits between the East and West retreats eastward, leaving more regions with negative net benefits. This trend can be inferred from Figures 4.16, 4.23, and 4.22, viewed in sequence.

As the results of this sensitivity analysis, it can be concluded that the gap between the ideal air leakage reduction levels assumed for retrofits aimed at complying with IECC 2018, and the actual reductions achieved in practice, significantly affects the estimated health and economic impacts. This difference should be carefully considered in any decision-making process.

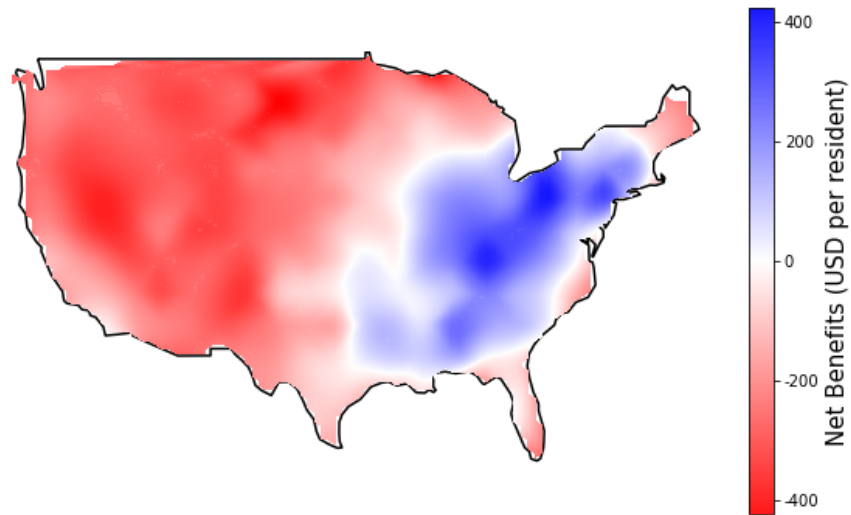


Figure 4.22: Illustrates the spatial distribution of the intervention year net benefits per-resident of single-family homes resulting from an on average 20% reduction in air leakage (R20) of all single-family homes.

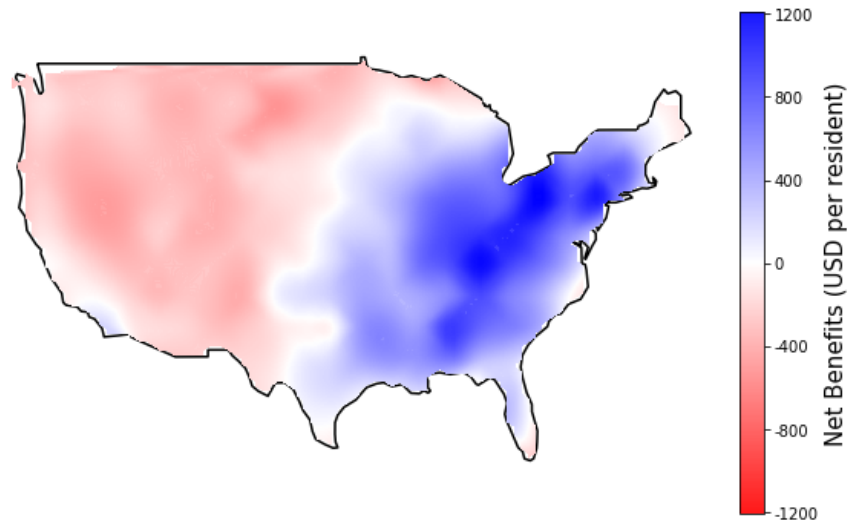


Figure 4.23: Illustrates the spatial distribution of the intervention year net benefits per-resident of single-family homes resulting from an on average 40% reduction in air leakage (R40) of all single-family homes.

4.2.2 Sensitivity Analysis of Uncertain Input Variables

This study lastly tries to identify the sensitivity of the final results uncertainty to each uncertain input variable. Consequently, Monte Carlo Simulations (MCS) were executed again, isolating each uncertain input variable to assess its impact on the final outcomes. Table 4.5 outlines the different scenarios designed for this evaluation, while Table 4.6 presents the outcomes of each simulation in terms of variance reduction with respect to the variable that was fixed.

As shown in Table 4.5, the scenarios are organized into three categories: “PM_{2.5} Reduction”, which represents the national average reduction of indoor PM_{2.5} of outdoor-origin due to the intervention; “Avoided Mortality”, which indicates the total national avoided premature mortality as a result of the intervention; and “Net Benefits”, which is the total national net benefits from the intervention. These three outputs are selected because they represent the final results generated at each step of the integrated model. They arise from the mass balance model, health impact model, and economic model, respectively. Also, each is influenced by a different set of inputs, which enables the targeted analysis of each output in relation to the inputs that affect it.

Table 4.5: Summarizes the sensitivity scenarios designed to evaluate the impact of uncertain input variables on the uncertainty of a target output. These scenarios are all based on the “IECC ALL” scenario, as defined in 4.1.

Scenario	Target Output	ACH ₅₀	P	K	β	VSL	Price Parameter
P1-K	PM _{2.5} reduction	U ^a	U	F ^b	U	U	U
P2-P	PM _{2.5} reduction	U	F	U	U	U	U
P3-ACH ₅₀	PM _{2.5} reduction	F	U	U	U	U	U
M1-!β	Avoided Mortality	F	F	F	U	U	U
M2N1-β	Avoided Mortality and Net Benefits	U	U	U	F	U	U
N2-VSL	Net Benefits	U	U	U	U	F	U
N3-C	Net Benefits	U	U	U	U	U	F

^aU: The variable has an Uncertain value during simulation.

^bF: The variable has a Fixed value during simulation.

Inferences from Figures 4.24, 4.25, and 4.26, along with Table 4.6, reveal that Scenario P2-P, which stabilizes the penetration factor, results in the most substantial variance reduction of 98.95% and greatly affects the uncertainty of the reduction of indoor PM_{2.5} of

outdoor-origin under intervention. Furthermore, the value for β (M2N1- β) significantly impacts the total premature mortality avoided uncertainty, achieving a 90.62% variance reduction. Additionally, the VSL (N2-VSL) has the most pronounced effect on the net benefits uncertainty, with a 93.4% reduction.

Table 4.6: Summarizes the percentage of variance reduction in a given output for each scenario defined in Table 4.5 compared to the “IECC ALL” scenario outlined in Table 4.1.

Scenario	Indoor PM_{2.5} (σ^2 reduction)	Mortality Avoided (σ^2 reduction)	Net Benefits (σ^2 reduction)
P1-K	9.27%	—	—
P2-P	98.95%	—	—
P3-ACH ₅₀	0.46%	—	—
M1-! β	—	-4.67%	—
M2N1- β	—	90.62%	2.00%
N2-VSL	—	—	93.40%
N3-C	—	—	-26.96%

In some cases, fixing a variable can lead to an increase in uncertainty. For instance, fixing costs results in approximately a 27% increase in variance (N3-C), and stabilizing variables that affect mass balance uncertainty leads to a 4.67% increase in variance (M1-! β) and a wider range of results. This phenomenon can be explained in two ways. Firstly, negative correlations may occur when a variable is negatively correlated with the primary output and acts as a counterbalancing factor, reducing overall variance, such as in the N3-C scenario where the price parameter is negatively correlated with net benefits. Secondly, stabilizing effects that involve variables providing more comprehensive coverage of the system’s dynamics, such as in scenario M1-! β , can capture mitigating factors or balancing forces, thus reducing the variability of the output.

This sensitivity analysis identified the variables with the greatest influence on the uncertainty of outputs. It highlights their importance in shaping the spectrum of final results and emphasizes the need to specify these values as accurately as possible, and to consider their implications for robust decisions.

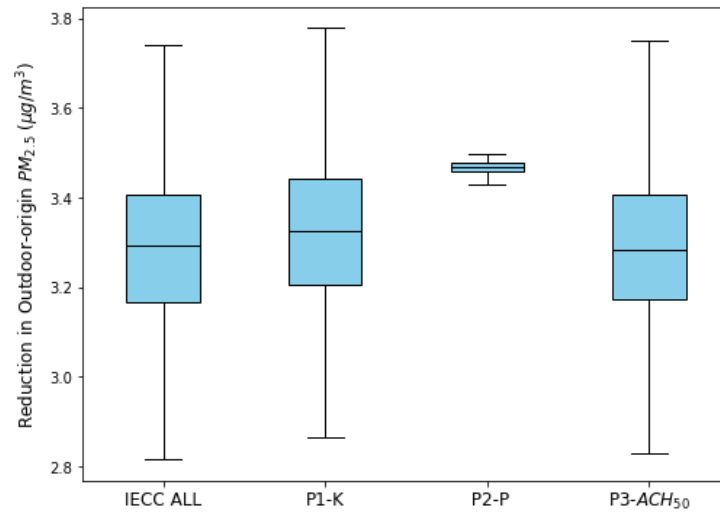


Figure 4.24: Displays the value and uncertainty of the reduction in indoor $PM_{2.5}$ daily mean from outdoor sources within the related scenarios defined in Table 4.5 compared to results from “IECC ALL” scenario.

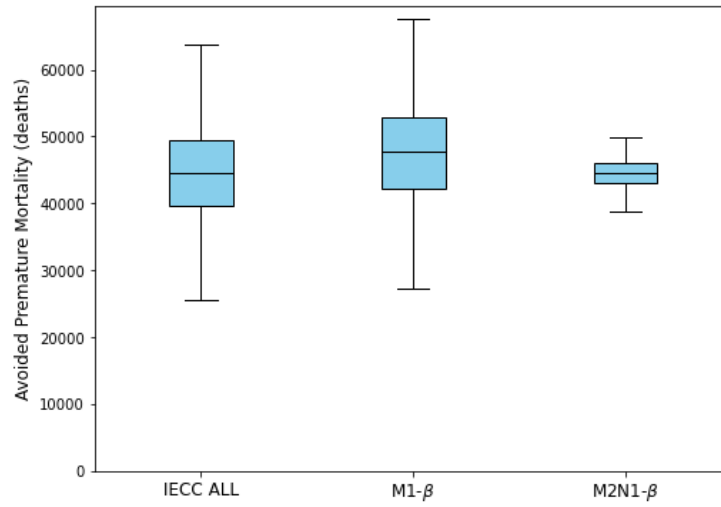


Figure 4.25: Illustrates the value and uncertainty of the annual avoided premature mortality within the related scenarios defined in Table 4.5 compared to results from “IECC ALL” scenario.

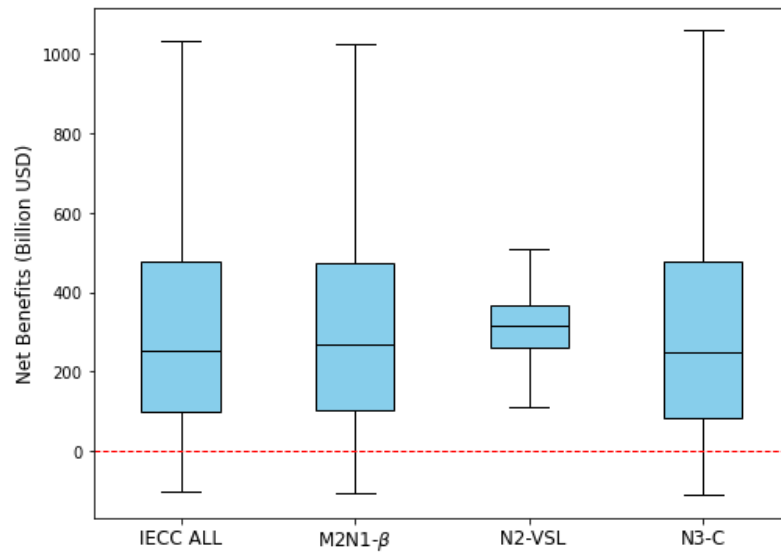


Figure 4.26: Illustrates the value and uncertainty of the intervention year total net benefits within the related scenarios defined in Table 4.5 compared to results from “IECC ALL” scenario.

Chapter 5

Concluding Remarks

5.1 Conclusion

This study aimed to investigate the health and economic impacts of improving buildings' airtightness. Specifically, it focused on reduced exposure of residents to outdoor-origin $\text{PM}_{2.5}$. It contributes to research on the impacts of enhancing buildings and their protective role against outdoor-origin $\text{PM}_{2.5}$, addressing a critical gap in understanding how modifications in building airtightness can mitigate the health risks associated with outdoor-origin $\text{PM}_{2.5}$ in residential environments.

To achieve this objective, an integrated modeling framework was developed by this study, utilizing concepts in mass balance modeling, health impact modeling, and economic modeling, then adjusting and combining them to create the framework. This study defined the scope of the analysis to be the period of 1980-2010 across the contiguous United States, at a resolution of $1.9^\circ \times 2.5^\circ$. Single-family homes were chosen as residential buildings to be studied since they accommodate most Americans. Data was gathered and processed, including residential stock data, population, baseline mortality, VSL, and leakage reduction price information. The residential stock data was segmented based on building type and vintage. The framework employed a time-averaged mass balance model to calculate the infiltration factor for each residential segment in each grid cell. It then used these infiltration factors to calculate the difference in outdoor-origin $\text{PM}_{2.5}$ between the baseline and intervention scenarios for each segment. Subsequently, a modified concentration-response function was used to compute changes in mortality risk and the total premature mortality avoided. Finally, the cost of interventions based on the level of leakage reduction and

the benefits from lives saved were calculated, with results presented both regionally and nationally.

The findings of this research indicate significant health benefits from reduced exposure to outdoor-origin $\text{PM}_{2.5}$ due to improving single-family homes airtightness. The results show that the current single-family home stock requires an average of 79% leakage reduction to comply with IECC 2018, leading to an average of $3.28 \mu\text{g}/\text{m}^3$ reduction in daily mean concentrations of outdoor-origin $\text{PM}_{2.5}$ in single-family homes across the United States. This reduced exposure to outdoor-origin $\text{PM}_{2.5}$ causes potential health benefits as high as 44,611 (29,831, 58,905) lives saved annually and \$355 (\$45, \$1173) billion in 2020 USD in benefits nationally. The results show that it is likely that the health benefits of intervention will exceed the costs, resulting in \$251(-\$62, \$1067) billion in 2020 USD of net benefits nationally in the intervention year.

The highest net benefits are achieved by bringing buildings of all vintages into compliance. However, residences built between 1940-1980 offer the highest net benefits of the three vintages explored. This is due to a combination of the leakiness of older buildings, and the larger number of relatively newer buildings. However, because the older buildings are so leaky, it is also shown that improving older buildings offers the most net benefits for their residences. Improving buildings built prior to 1940 yielded a net benefit of \$2,263 in 2020 USD on average, compared to \$2,239 for buildings constructed between 1940 – 1980 and \$1,439 for buildings constructed after 1980.

The results also offer insightful findings regarding the spatial distribution of these benefits, suggesting that the benefits are the highest in the eastern U.S. and showing that despite the overall benefits outweighing the costs, the costs could exceed the benefits in the western part of the United States.

The study also investigated the possible outcomes that may occur in practice when energy and weatherization-oriented retrofits yield lower leakage reduction. The findings show that the health benefits of leakage reductions in levels as low as 20% are still significant; however, the net benefits are likely to be positive for reduction levels higher than 25%.

This study presents a framework that enables fine-resolution spatial analysis together with national-wide analysis for health and economic impact assessment of residential building airtightness improvements. A further technical implication of this study is that the framework could be easily modified for a wider range of scenario analyses, including other building improvement measures such as particle removing mechanisms, offering adaptability and fine spatial resolution compared to other studies in the domain.

The policy implications of this study are profound, bridging the gap between building airtightness and human health, thus providing valuable insights for policymakers engaged

in legislative and regulatory development. This research enables policymakers to consider building standards and codes not just from the traditional standpoint of energy efficiency but also through the lens of mitigating air pollution-related health impacts. Ultimately, this framework serves as a tool for developing policies that enhance indoor air quality and public health, encouraging a holistic approach to urban planning and building design.

5.2 Limitations and Future Works

This section focuses on enumerating the study’s limitations, suggesting pathways to tackle those limitations, and proposing ideas for future studies.

Regarding the results of this study, the lower bound of the net benefits under all simulated scenarios, including the IECC ALL scenario, falls below zero. This outcome complicates confidently asserting that improvements in airtightness will yield greater benefits than costs in the intervention year. Additionally, this analysis does not consider the potential decay of airtightness or maintenance costs, which limits the analysis to the intervention year. Incorporating models of airtightness decay and maintenance costs would enable reflection of the impacts over multiple years, rather than a static snapshot based on average daily air pollution levels during the study period. For example, simulations over five years beyond the intervention year, would likely see greater increases in benefits compared to costs and potentially shift the range of net benefits into positive territory, reported as the present value of net benefits over multiple years, considering discounting and inflation.

As part of the limitations, some modeling decisions are based on assumptions that, if further attention is given, can increase the reliability and accuracy of the results. These assumptions consist of certain decisions regarding choosing the correct distributions for uncertainty modeling or using national average values instead of spatially specific values in some calculations.

Parameters such as deposition rate and penetration factor exhibit considerable uncertainty across different buildings. The literature has suggested various distributions for these parameters, as explained in Section 2.3. However, this study employs only one distribution for each, despite the availability of multiple options. Conducting a sensitivity analysis in future works using multiple distributions reported in the literature could offer further insights into potential uncertainties.

Additionally, as demonstrated in Section 4.2.2, the value of relative risk or β significantly influences the resulting health impact. In this study, the health impact assessment is based solely on relative risk and β from Krewski et al. (2009), but there is a broader range

of relative risk and β values reported in the literature, as mentioned in Section 2.4.3. These relative risk values for the increase in long-term all-cause mortality associated with PM_{2.5} can dramatically affect the final health benefit estimates. Noting that Krewski et al. (2009) tends to provide lower effect estimates than much of the literature, health benefits could be underestimated. Therefore, conducting a sensitivity analysis on different relative risk or β values could reveal significantly different health impacts, highlighting the importance of including such analyses in future studies.

Furthermore, certain simplification assumptions related to the spatial variations of Ψ and ϕ values could be refined in future studies to achieve more accurate results. As discussed in Section 3.2.4, Ψ is calculated based on the infiltration factor of micro-environments that the general population spends their time in and the time budget of the population within those environments. Future research could enhance the calculation of Ψ in two ways: first, by accounting for spatial variations in time budgets and infiltration factors; second, by incorporating the uncertainties associated with each of these parameters into the Monte Carlo simulation. Additionally, the ϕ values used were national averages. Given that the U.S. Census Bureau (2024) offers county-level information, future studies could incorporate spatial variations for ϕ into the model to better reflect local conditions.

The cost modeling in this study was also constrained by relying on price information from a single source, which was quite general. For enhanced accuracy, future cost modeling should incorporate multiple sources to gather a broader range of data. Additionally, the current model does not account for spatial variations, even though construction prices and costs can vary significantly by location. Utilizing RSmeans construction cost data (2024) location conversion factor tables in future work could address these spatial variations. Furthermore, the uncertainty modeling of costs was based on limited information and certain assumptions regarding the symmetrical shape of the distribution, as detailed in Section 3.2.6. This limitation has impacted the quality of the cost uncertainty analysis, as evidenced by the narrow and constrained 95% confidence intervals observed in the results. These narrow bands occur despite the use of a triangular distribution which is designed to capture significant parameter uncertainty. Addressing these issues will be crucial for the reliability and comprehensiveness of the cost-benefit analyses.

In addition to improvements that can be made in the methodology, this study has established a solid ground for air pollution-related health and economic evaluation of improving residential buildings on a national scale with fine spatial resolution, which can be built upon to study a wide range of scenarios.

Firstly, this study accounts only for mortality as a health impact, not considering other morbidity effects. Although mortality comprises most of the health impacts associated with

PM_{2.5} exposure, it is possible to adapt the current model to assess other health endpoints quite easily.

As demonstrated in this study, improving building airtightness could lead to significant reductions in exposure to outdoor-origin PM_{2.5}, which infiltrates indoors. However, the broader picture might differ; increasing airtightness and thus reducing air change rates may lead to the accumulation of indoor-generated PM_{2.5}. In this scenario, if the accumulated amount of indoor PM_{2.5} outweighs the amount of outdoor PM_{2.5} infiltrated indoors, adverse health effects may occur instead of realizing health benefits. This situation is more likely to occur in areas with cleaner outdoor air. The accumulation of indoor-generated air pollutants is not limited to PM_{2.5}. Other pollutants, such as VOCs and radon, can also increase indoors with the improvement of airtightness (Kempton et al., 2022). Therefore, one limitation of this study is that the mass balance equations only account for outdoor PM_{2.5} that infiltrates indoors as sources and ignores indoor generated particles and pollutants. Due to concerns that increased airtightness may lead to a decrease in indoor air quality, it is crucial to consider indoor sources of air pollutants in some capacity in future works to avoid being misled in the decision-making process.

Additionally, the mass balance modeling used in this study considers particle removal by air change due to infiltration as the only loss factor. However, the residential stock is much more complex, and many buildings might have HVAC systems, mechanical ventilation, air filters, etc., which would change the mass balance equation sources and losses and ultimately impact the final estimated indoor exposure (Fisk & Chan, 2017a; D. Zhao et al., 2015).

The framework developed in this study facilitates consideration of these factors with minor modifications. To better understand these complexities, it is recommended that future research modify the mass balance model used in this study by incorporating additional data from ResStock and the literature to include factors that account for indoor-generated sources and other particle removal mechanisms and to conduct a more comprehensive analysis. The prospective analysis could compare various building upgrades to identify the most cost-effective improvement option or determine the optimal threshold for airtightness upgrades in each location, maximizing benefits while considering the accumulation of indoor-generated pollutants. Also, this analysis could further compare the use of portable air cleaners as an alternative or complement to building upgrades.

As highlighted in the results, Section 4.2, the leakage reductions achieved during energy retrofits are often limited. This study included a sensitivity analysis to account for different possible outcomes. However, building directly upon this research, examining intervention scenarios aligned with current weatherization and energy efficiency programs, and setting

airtightness improvement targets according to these programs not only provides a clearer picture of the health benefits, it also enables discussing the results from a co-benefit perspective, linking energy savings with health benefits, reinforcing the case for energy retrofit plans highlighting their dual advantages in terms of energy conservation and public health.

This study does not include population demographic-specific analysis; however, the framework supports the analysis of targeted interventions with the appropriate demographic data. Such analysis could be particularly useful for supporting more equitable and effective public health strategies and optimizing efforts to assist populations that could benefit the most. For instance, it could examine disparities in benefits received by households with different income levels and how these impacts are distributed spatially.

More on the use cases of the developed framework for other studies, the framework could be adapted by modifying model inputs such as population growth, baseline mortality rates, VSL, air pollution data, and the predicted increase in the number of buildings and their expected quality based on up-to-date standards to evaluate future scenarios. As climate change is expected to generally worsen the situation of ambient air pollution, the role of residential buildings in protecting the population will grow, emphasizing the necessity of such studies. Additionally, air quality alerts would rise, and people would seek refuge within their homes as part of an adaptive behavior (Sparks et al., 2024). The effectiveness of these adaptations would also rely on how much buildings are preventing pollution from reaching indoors. Combining the perspectives of such studies conducted by Sparks et al. (2024) and this thesis provides a clearer idea of what our building standards should be in the future to maximize the protection they offer us from outdoor air pollution.

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APPENDICES

Appendix A

Additional Material

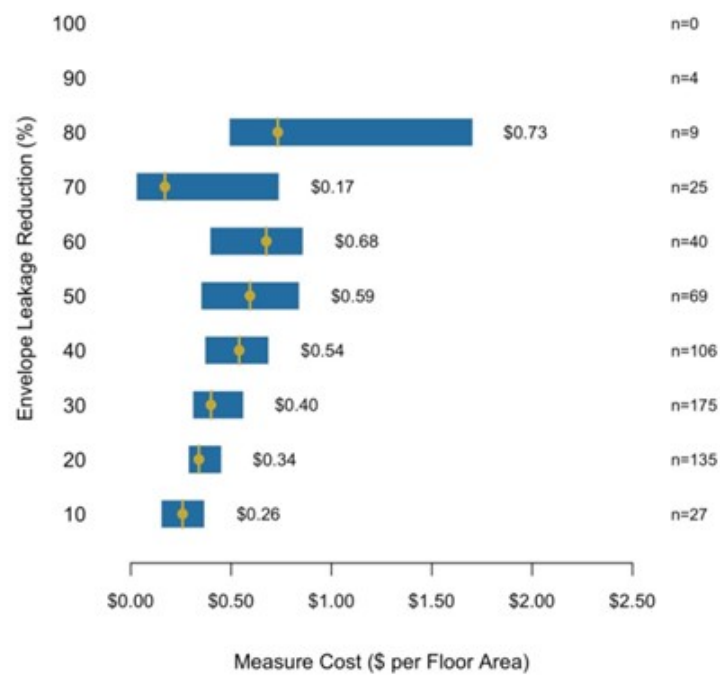


Figure A.1: Displays the envelope leakage reductions and associated air sealing costs from Less et al. (2021).

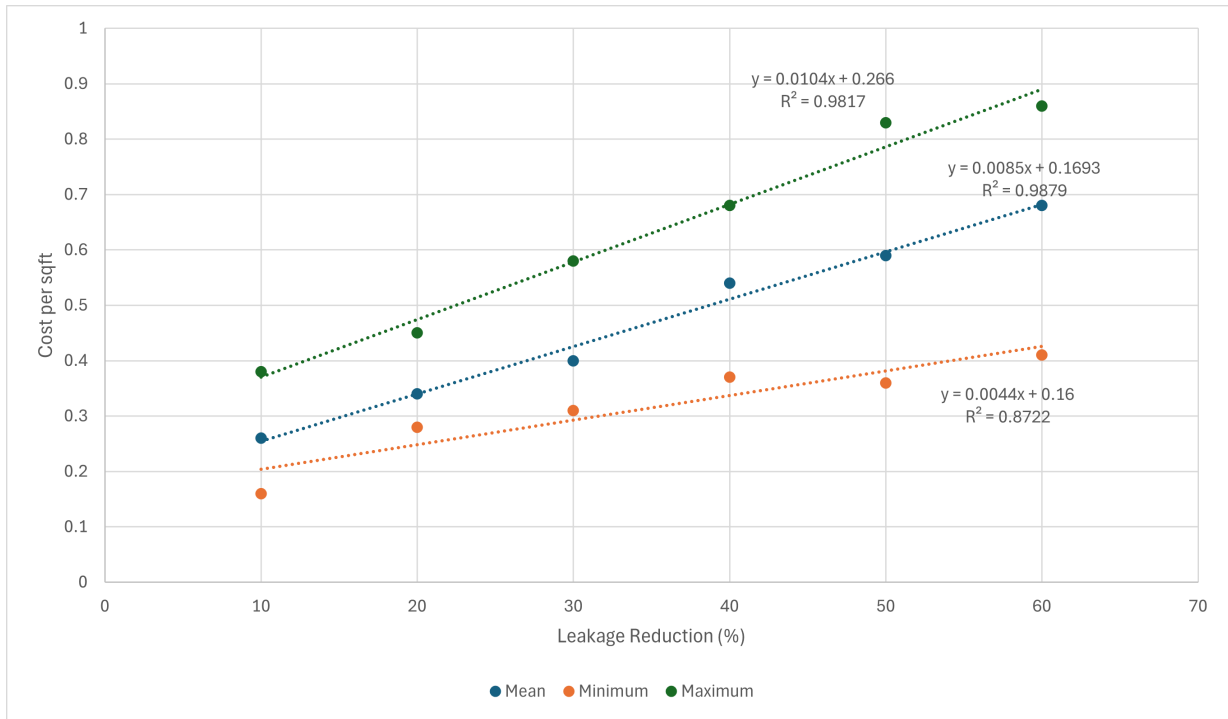


Figure A.2: Illustrates the linear regressions performed on the national average data points for air sealing cost data.

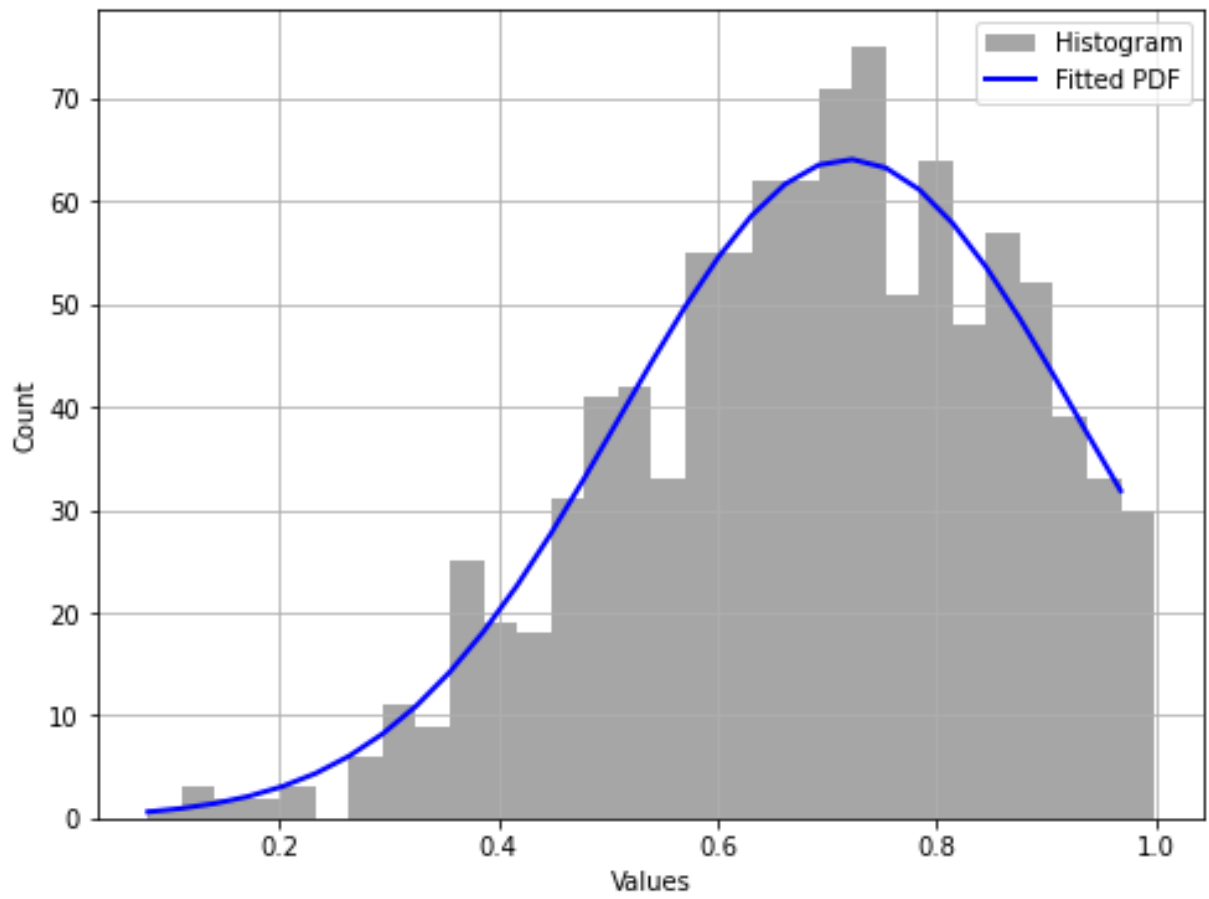


Figure A.3: Illustrates the distribution that the value for the penetration factor is sampled from in the simulations.

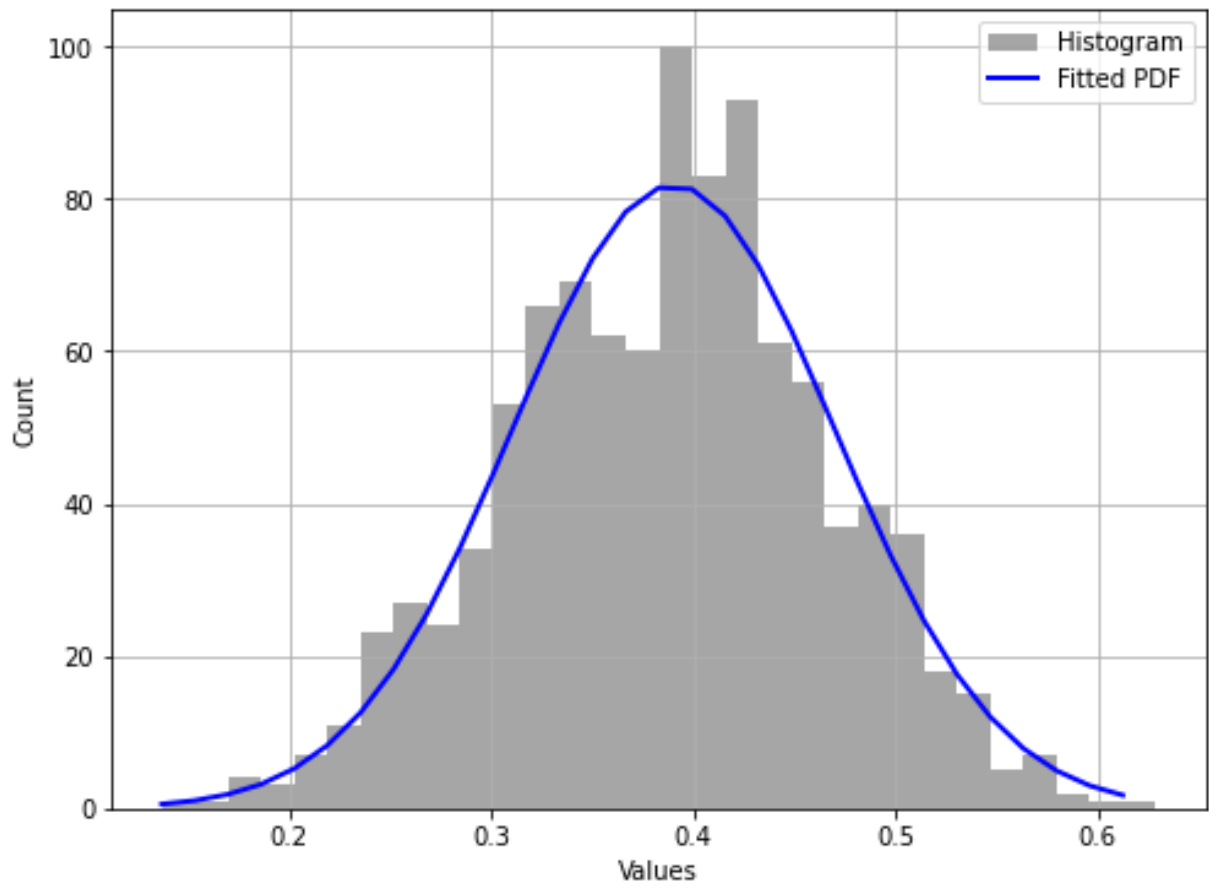


Figure A.4: Illustrates the distribution that the value for the particle deposition rate is sampled from in the simulations.

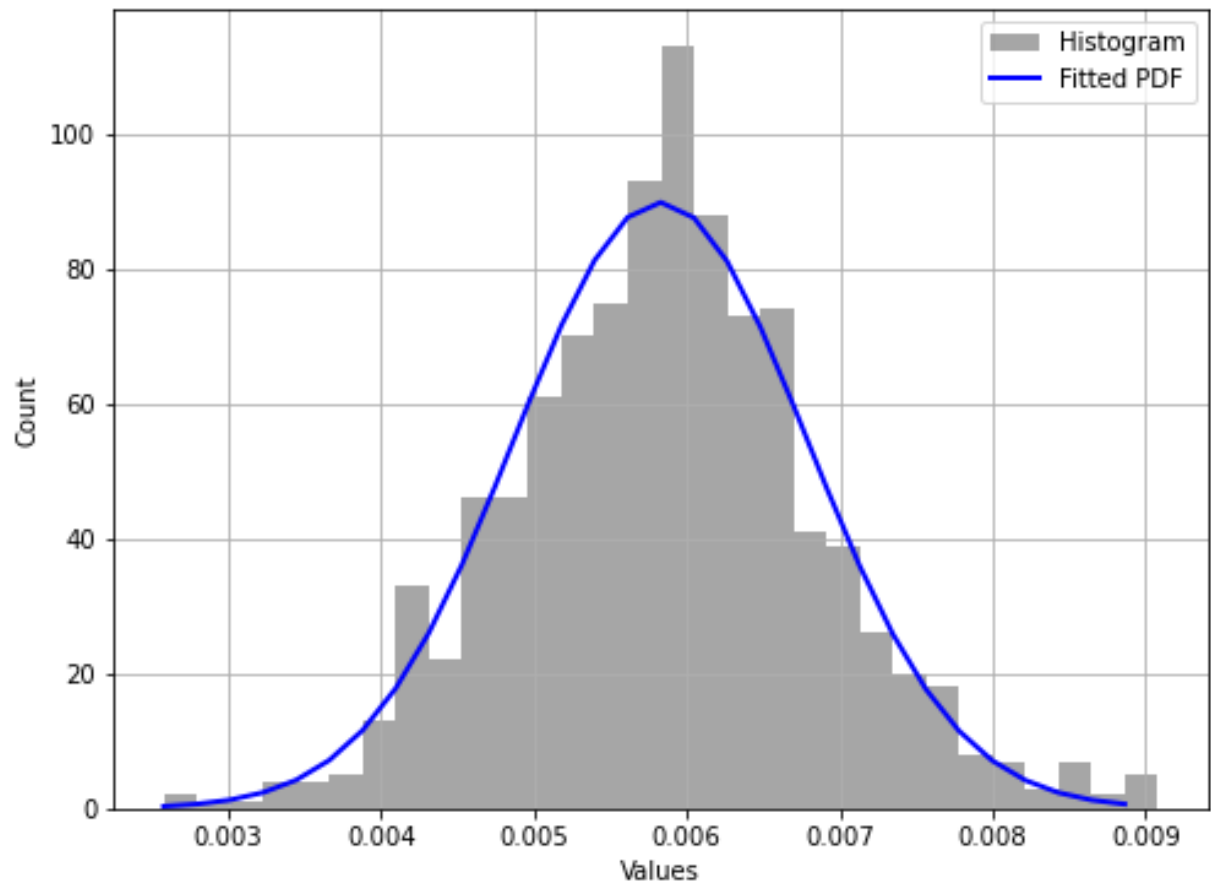


Figure A.5: Illustrates the distribution that the value for the β is sampled from in the simulations.

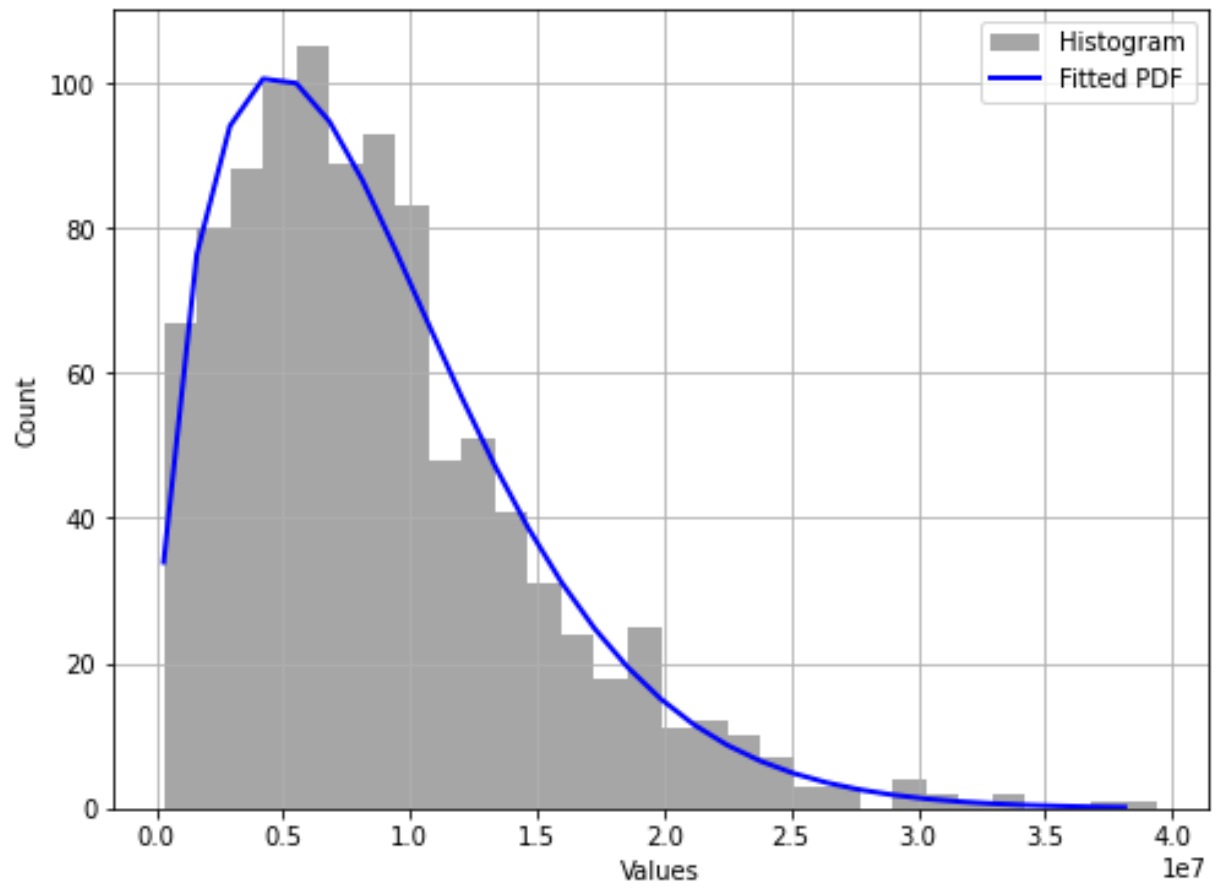


Figure A.6: Illustrates the distribution that the value for the VSL is sampled from in the simulations.