Assessing the Intersectional Risks Associated with the Full Life Cycle of the U.S. Housing Stock

By

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S.M., Massachusetts Institute of Technology (2021)
B.S., Boğaziçi University (2018)

Submitted to the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degree of

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Abstract

This work presents the most comprehensive framework to date to assess the intersectional risks associated with design and policy decisions regarding the built environment. This framework is applied to decisions regarding the selection of hazard mitigation measures to apply, households to prioritize in hazard mitigation grant programs, and construction materials to use in efforts to reduce societal greenhouse gas (GHG) emissions.

To study these decisions, a computation inexpensive method is developed to compute expected damages associated with each individual building in a community with hurricane wind exposure. This method is applied to study the cost burden of expected damages on each individual household. Later, this is integrated into building life cycle assessment (LCA) to incorporate hazard vulnerability into building embodied emissions. Lastly, building LCA is extended to inform the sectoral environmental footprint (SEF) of construction material sectors.

Together, the model results of this work show that expected damages are currently underestimated, socially-vulnerable groups are likelier to be priced out hazard repairs, and ignoring use and end-of-life stages leads to ignoring the largest portion of building life cycle emissions as well as the largest contributors of the SEF of construction materials. By reevaluating the performance of the housing stock under each metric, strategies are proposed to prevent monetary damages, redistribute the cost burden of remaining monetary damages, and couple considerations for climate mitigation and climate adaptation by promoting disaster risk reduction as a pathway towards GHG abatement.

Thesis Supervisors:
Franz-Josef Ulm—Professor of Civil and Environmental Engineering
Randolph Kirchain—Principal Research Scientist, Materials Research Lab

Dedicated to my parents Banu and Ozan Manav, who are both civil engineers and whose path I followed

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1 Introduction: Three Pillars of Sustainability

One of the United Nations' (UN's) Sustainable Development Goals (SDGs) is to "make cities and human settlements inclusive, safe, resilient, and sustainable" (UN, 2015). To aid design and policy towards this goal, it is crucial to have a framework capable of assessing the performance of the housing stock in the face of economic, social, and environmental stressors. Each of these elements corresponds to one of the three pillars of sustainability.

This work presents the most comprehensive framework to date to assess the intersectional risks associated with design and policy decisions regarding the built environment. The chapters of this work demonstrate the proposed methods on decisions regarding the selection of hazard mitigation measures to apply (**Chapter 2**), households to prioritize in hazard mitigation grant programs (**Chapter 3**), and construction materials to use in efforts to reduce societal greenhouse gas (GHG) emissions (**Chapters 4 & 5**).

In **Chapter 2**, an updated framework is developed to compute expected damages associated with each individual building in a community with hurricane wind exposure. In **Chapter 3**, this framework is applied to study the cost burden of expected damages on each individual household and identify trends across socioeconomic and demographic groups. In **Chapter 4**, this is integrated into building life cycle assessment (LCA) to incorporate hazard vulnerability into building embodied emissions. In **Chapter 5**, industrial ecology tools like life cycle inventories (LCIs) and building LCA are extended to inform the sectoral environmental footprint (SEF) of construction materials sectors.

Chapter 2 mainly focuses on the economic pillar of sustainability, **Chapter 3** on the social pillar, and **Chapters 4 & 5** on the environmental pillar. Each chapter of this work highlights benefits of assessment methods found under other pillars. This work attempts to bridge the disconnect between available assessment methods by combining stressors and metrics across the three pillars of sustainability.

2 Contributions to Economic Assessment

This chapter includes the manuscript "Texture-Informed Approach for Hurricane Loss Estimation: How Discounting Neighborhood Texture Leads to Undervaluing Wind Mitigation" authored by Ipek Bensu Manav, Jacob Roxon, Franz-Josef Ulm, Jeremy Gregory, and Randolph Kirchain (Manav et al., 2022).

2.1 Abstract

Motivating investment in pre-disaster mitigation requires accurate estimates of natural hazard risks. Present tools for loss estimation overlook building-level variations in wind loading induced by the configuration of surrounding buildings, called neighborhood texture. In doing so, such tools underestimate expected wind-related losses and undervalue wind mitigation.

In this manuscript, texture effects are incorporated into a widely recognized loss estimation framework and applied to a case study of the residential building stock in Florida – with a focus on five densely populated counties representing a range of hazard exposure. For this study, each building is individually assessed for its prevailing local texture, and its occupancy and building characteristics are probabilistically assigned based on current Census data. Mitigation measures considered include shutters, straps, and tie downs.

Even accounting for more than a third of homes already having these mitigation measures, model results suggest that implementing them would yield annualized benefits of $4.3 billion statewide ranging from $136 per household in Duval County to $1,950 per household in Miami-Dade County (respectively 100% and 90% higher than conventional estimates).

2.2 Keywords

Hurricanes, Loss Estimation, Texture

2.3 Introduction

Over the last four decades, tropical cyclones have caused nearly $1 trillion in losses in the United States – more than any other natural hazard (NOAA 2020). As costs mount, stakeholders are calling for more focus and spending on pre-disaster mitigation rather than response and recovery (Gall et al., 2011). In fact, a recent report by the National Institute of Building Sciences (NIBS) estimated that $14 billion spent by Federal agencies in the past 23 years to mitigate wind-related hazard risks will yield $70 billion in avoided property losses – a cost-to-benefit ratio of 1 to 5 (NIBS 2019a; 2019b). The U.S. National Science and Technology Council (NSTC) identified six grand challenges in creating resilient communities. Four of these grand challenges deal with doing a better job at quantifying and communicating hazard risks and the value of mitigation within communities (NSTC 2008; 2005).

There are a number of tools communities can turn to for quantifying hazard risk by predicting expected losses due to natural hazards. For wind-related hazards, the two most widely used are the HAZUS-MH model developed by the U.S. Federal Emergency Management Agency (FEMA) (Schneider & Schauer, 2006; Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006) and the Florida Public Hurricane Loss Model (FPHLM) developed by a consortium of Florida universities led by Florida International University (FIU) (Pinelli et al., 2011). Within such tools, a key determinant of loss is the expected wind load experienced by a structure. Expected wind loads derive from both the local rate of occurrence of storms and the morphology of the local neighborhood and nearby obstructions, referred to as terrain (ASCE 2016; 2010). Present models of terrain effects consider obstruction height and density, and average these values across an upwind fetch of several kilometers (Wieringa, 1992, 1993) leading to nearly identical damage and loss risk levels for buildings within the same area. Previous work by several of the authors has shown that the fine characteristics of the configuration of surrounding buildings, called neighborhood texture, create local variations in wind loads. As a result of texture, some buildings experience loads far above conventional estimates and some far below (Roxon, 2020). This manuscript shows that, because structural response is highly non-linear, by ignoring these variations, conventional methods systematically underestimate expected losses and, therefore, undervalue wind mitigation. On state level, this undervaluation could be on the order of billions of dollars per year.

2.4 Literature Review

There are a number of studies and models for loss estimation (also called risk assessment) that assess structural performance under wind loading and evaluate expected wind-related losses. Models of this type can be grouped into two categories based on the underlying approach: econometric models (e.g., fitting claims data to directly infer a relationship between building characteristics and loss exposure) and engineering-based models (e.g., simulating building loss exposure based on structural analysis) (Pita et al., 2013). Engineering-based models span a range of scales from building components (e.g., roof panels and roof-to-wall connections) (Li & Ellingwood, 2006) to representative building types (e.g., wood-frame single family dwellings) (Li & van de Lindt, 2012). These models can be employed to explore the implications of damage on different scales, including groups of these representative building types aggregated within Census Tracts (Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006), counties (Pinelli et al., 2011) or actuarial portfolios (AIR 2019; ARA 2019; CoreLogic 2019; RMS 2019). These models can also be incorporated into optimization algorithms for performance-based design (Wen & Kang, 2001a, 2001b). Engineering-based models have been applied to the cost-benefit analysis of applying various mitigation measures (Torkian et al., 2014) and the life cycle cost analysis (LCCA) of mitigating low-rise (Dong & Frangopol, 2017; Li, 2012; Noshadravan et al., 2017) and mid- to high-rise buildings (Mahmoud & Cheng, 2017).

While a variety of data sources (e.g., field observations, wind tunnel tests, or claims data) and analytical methods (e.g., regression) have been employed in developing engineering-based models, these models are notionally similar in how they treat the influence of nearby obstructions (e.g., buildings and vegetation) on wind loads. Specifically, these models make use of various land use land cover (LULC) databases (e.g., the Florida Water Management Districts and the Multi-Resolution Land Characteristics (MRLC) Consortium) to infer information on nearby obstructions and aggregate this information on various scales (e.g., Census Tract in HAZUS and ZIP code in actuarial tools), but they essentially refer to the same guidelines (Powell et al., 2003; Vickery et al., 2009; Vickery & Skerlj, 2005) for the treatment of this information. For these guidelines, they either refer to local building codes (AIR 2019) or they refer to the same authors that contributed to the development of building codes (ARA 2019; CoreLogic 2019; RMS 2019). The American Society of Civil Engineers (ASCE) 7 wind load provisions are the basis for building codes effective across the U.S. (ICC 2020; 2019; 2017).

Nearby obstructions interfere with wind flows and affect wind loads (or pressures) acting on structures. In wind load provisions, this interference is captured within the impacts of what is referred to as terrain (also called exposure or surface roughness). When computing expected wind loads, the local terrain determines the exposure factor, K_h, at mean roof height h, applied as follows

$$q_h \propto K_h v^2 \qquad \text{Eq.1.4.1}$$

where q_h is the velocity pressure at h, and v is the 3-s gust wind speed at the height of 10 m (33 ft) in open terrain (Zhou & Kareem, 2002). In literature, K is recognized to be a continuous function of the surface roughness length, z_0 (m) (Wieringa, 1992, 1993) where z_0 is derived from the average height and areal density of nearby obstructions (Lettau, 1969). Recent studies have developed analytical relationships between K and z_0 using wind tunnel tests (Ozmen et al., 2016), as well as Monte Carlo (MC) (Datin & Stedman, 2015), finite element (FE) (He et al., 2017) and computational fluid dynamics (CFD) simulations (Kent et al., 2017; Ricci et al., 2017). However, in current practice, K_h is assigned one of four discrete values corresponding to four terrain classes, namely Exposure A (urban), Exposure B (suburban), Exposure C (open terrain) and Exposure D (water surfaces). Comparatively denser (or rougher) terrain classes correspond to muted wind loading (Wieringa, 1992, 1993).

Over the last three decades, since its creation, the ASCE 7 provisions have been revised seven times (Barben & Solnosky, 2017). Although changes have been made to the definitions of factors that add onto **Eq.1.4.1** and the wind speeds that **Eq.1.4.1** is based on, these changes have not materially affected how terrain is accounted for (Cook et al., 2011). Critique on terrain classes have consisted of elimination (Vickery & Skerlj, 2000) and reintroduction of Exposure D (Vickery et al., 2010), and calling for (Irwin, 2006) and proposing (Ellison & Rutz, 2015) systematic approaches for assignment which currently relies on expert judgment (Ellingwood & Tekie, 1999).

Of tools for loss estimation, HAZUS is the basis for most large-scale cost-benefit reports (NIBS 2019b). It also contains the first nationwide database for z_0 assigned systematically. This assignment makes use of LULC maps (FDEP 2021; MRLC Consortium 2015). Each LULC category corresponds to a z_0 (Vickery, Lin, et al., 2006). In other loss estimation tools, similarly, z_0 is derived from LULC maps. Typically, z_0 is then used to adjust wind speeds and adjusted wind speeds are input to damage and loss functions (AIR 2019; ARA 2019; CoreLogic 2019; RMS 2019). In HAZUS, however, these functions are differentiated by characteristic values of z_0 (Vickery, Skerlj, et al., 2006). These functions were developed from wind tunnel tests (Case & Isyumov, 1998; Ho et al., 1992) that were conducted on regularly spaced arrays of similar low-rise buildings. Such regularity (in spacing and footprint area) is a common thread in terrain studies.

Summary tables for z_0 are available for stretches of terrain identified as continuous and homogeneous over areas of hundreds or thousands of meters in fetch (Wieringa, 1993). In HAZUS, and other tools, inhomogeneous areas are broken down into relatively homogeneous stretches and then z_0 are averaged (so constant) across the area as a whole (e.g., weighted by building footprint in HAZUS and by population in actuarial tools) (Vickery, Lin, et al., 2006). This simplification is a practical one, driven by a lack of an established means to quantify inhomogeneity (and its impacts) on finer scales. As a consequence, current loss estimation tools have limited ability to evaluate the influence of surrounding buildings on damage (e.g., through shielding or tunneling) (Pita et al., 2015).

Recently, Roxon demonstrated the use of the radial distribution function (RDF) as a computationally tractable method to quantify the impact of inhomogeneity at finer scales (Roxon, 2020). In statistical physics, this function describes variations in the density of atoms surrounding an atom of interest. Hence, this function provides a succinct measure, referred to by Roxon as texture, of disorder and density in the configuration of surrounding buildings within fetches of only tens of meters. Roxon replicated the morphologic characteristics of real-life cities in CFD simulations, by varying both spacing (based on the local RDF) and footprint areas (based on the local distribution) for groups of square-shaped buildings, and developed an empirical relationship between texture and wind loading on building facades. (Further characterization of the literature on terrain and texture can be found in the **Supplementary Materials**.)

In summary, the literature on loss estimation is extensive. Most of that literature applies a similar set of assumptions around structural wind loading, which do not account for the local configuration of surrounding buildings (i.e., texture). Roxon's texture represents a computationally inexpensive method to account for local configuration, but it has not yet been adapted for loss estimation. This manuscript aims to fill these gaps by incorporating a texture-based model into a loss estimation framework, and applying that framework to explore the implications of neighborhood texture on estimates of expected losses and the derived value of wind mitigation.

To accomplish this goal, we introduce a procedure for deriving probabilistic, directional multipliers on wind speeds that approximate the impacts of local configuration, and we incorporate these multipliers into HAZUS – a widely used loss estimation tool. Its role for policy in emergency management makes it relevant for large-scale studies that could inspire public discourse. Also, HAZUS is publicly accessible and modifiable, and, although private actuarial tools may be more advanced, HAZUS includes many of the aspects necessary for this analysis (e.g., wind speed distributions and damage and loss functions). Here, it is also important to note that, unlike these actuarial tools, loss values in HAZUS do not reflect deductibles and limits, hence losses are a representation of monetary damage. Because no public dataset includes all building-level information needed to carry out this analysis, we probabilistically assign occupancy and building characteristics to building footprints.

2.5 Methodology

To estimate the expected wind-related losses for any building, it is necessary to know its expected wind loads and its construction characteristics (Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006). To incorporate the variations created by neighborhood texture, we must also know details about the arrangement of nearby buildings. Unfortunately, the authors are unaware of any publicly available dataset that provides all of this information for individual buildings in the U.S. However, geographic information system (GIS) datasets are available that describe the location and footprint (and occasionally three-dimensional envelop) of buildings. Separately, Census data is available on the prevalence of occupancy and building types. In the U.S., the highest resolution form of the latter data is available for Census Tracts. Each Census Tract averages 4,000 inhabitants and is designed to be homogeneous in regard to demographics and living conditions (U.S. Census Bureau, n.d.-b).

To accommodate the state of the data, our methodology comprises four elements: [1] The use of GIS files to evaluate the local texture for each building in the area of interest (**a** of **Figure 2.5-1**), [2] the incorporation of local texture into the recurrence of wind loads acting on each building (**b** of **Figure 2.5-1**), [3] the construction of probability distributions (called building schemes) to describe building structural response from the likelihood of occupancy and building types in the area of interest (**c** of **Figure 2.5-1**), and [4] the integration of all this information to estimate expected wind-related structural losses (**d** of **Figure 2.5-1**) and the benefits of mitigation to reduce those losses.

Evaluating Local Texture and Its Impact on Building Drag Coefficients

To estimate the impacts of texture on expected structural losses, we first evaluate the local textural characteristics surrounding a building and how they amplify or mute the drag coefficient experienced by that building. Ideally, this would be carried out using CFD simulations of each individual building within the study area. Unfortunately, at present, the computational cost of CFD simulations is prohibitive for large case studies. Instead, we make use of an empirical relationship developed by Roxon (2020) (discussed below) and use that to augment current algorithms described in the ASCE 7 provisions and HAZUS framework. This relationship specifically estimates the maximum drag coefficient experienced by a building accounting for the configuration of nearby structures.

Roxon developed this relationship by first executing CFD simulations for hypothetical neighborhood configurations, and then creating a regression model between attributes of these neighborhoods and the drag coefficients induced on neighborhood buildings. Specifically, Roxon found that the maximum drag coefficient is well predicted by the frontal (or facade) density for a building of interest and the angular order, ϕ, of its surrounding buildings. ϕ is used in statistical physics to describe the disorder (or order) in atomic arrangements. To make the regression model easier to apply, Roxon found that ϕ is strongly correlated with the number of surrounding buildings. These findings have been applied in this work.

For each building b in the study area, the latitude and longitude of the building centroid and the building footprint area, A_b (m^2), are extracted from GIS files of building footprints. For the study area, an overall density length, $\hat{L}$ (m), is estimated as the average of $\sqrt{A_b}$ across all buildings. Using this value, the local neighborhood of b is defined as comprising buildings within a radius of $10\hat{L}$. For this neighborhood, two attributes of b are estimated. These are the local areal density, P_b (buildings per m^2), and the local density length, L_b (m). The product of these two attributes and the average building height, h, (i.e., $P_b L_b h$) provides an approximation of neighborhood frontal density. Additionally, the number of neighbors, n_b, is computed as the buildings within a radius 3.5 L_b of b. n_b was found to be strongly negatively correlated with ϕ and represents a measure of disorder (Roxon, 2020). These attributes are then used to derive the maximum drag coefficient specific to b, C_b, using a relationship defined by Roxon (2020). Formally, this is stated as:

$$C_b = n_b\sqrt{P_b L_b h} + 1 \qquad \text{Eq.1.5.1}$$

As a point of comparison, the drag coefficient of an isolated square-shaped building, C_0, is 2 (*Drag Coefficient*, 2004). When $C_b > C_0$, a structure experiences texture-induced amplifications in wind loading, and $C_b < C_0$ implies texture-induced reductions in loading. **Figure 2.5-2** illustrates differences in local texture and the consequences of that difference on drag coefficients for three adjacent Census Tracts in Broward County, Florida. The greatest potential amplifications of C_b are for buildings in areas with high density (high $P_b L_b h$) and low disorder (low n_b). In **Figure 2.5-2** this occurs within the southernmost Census Tract (extensive orange coloration of buildings). The greatest potential reductions of C_b are for buildings in areas with low density and high disorder. In **Figure 2.5-2** this occurs within the northernmost Census Tract (blue coloration of buildings). Areas with medium density and disorder exhibit a mix of amplifications and reductions.

Incorporating Texture-Adjusted Drag Coefficients in Wind Loads

In Chapter 16 Section 9 of the ASCE 7 provisions, the derivation of wind loads experienced by a building b begins by identifying the far-field 3-s gust wind speeds (v_b^B , referred to as the basic gust wind speeds, or basic gusts, and defined by gusts occurring in the wind layer high enough above ground surface to be unaffected by frictional forces created by the local terrain) at the centroid of the Census Tract containing b (Cook et al., 2011; Vickery, Skerlj, & Twisdale, 2000; Vickery, Skerlj, Steckley, et al., 2000). The provisions also give guidelines on adjusting these basic gusts to local gusts (v_b^L) based on the prevailing local terrain. Using that, it is possible to identify a factor, called the wind speed ratio, W , that represents the ratio between local and basic gusts. This leads to the relationship

$$v_b^L = W_b v_b^B \qquad \text{Eq.1.5.2}$$

where W is the square-root of the exposure factor, κ , from **Eq.1.4.1** (Cook et al., 2011).

To account for the impact of neighborhood texture, we estimate building-specific **effective** gusts (v_b^{eff}). The effective gusts aim to represent wind loading deviations from local gusts due to recirculation eddies (and resulting pressure differentials) induced by the configuration of buildings (and neighborhood canyons) surrounding b . Formally, therefore, we define the relationship between v_b^{eff} and v_b^L as:

$$v_b^{eff} = eW_b v_b^L \qquad \text{Eq.1.5.3}$$

where eW_b is a proportionality constant that will be referred to as the effective wind speed ratio.

To estimate expected losses, we use the HAZUS framework which does not explicitly compute local gusts, but rather maps basic gusts to expected damage and losses for five terrain descriptions, namely “Open” (z_0 = .03 m), “Lightly Suburban” (z_0 = .15 m), “Suburban” (z_0 = .35 m), “Lightly Treed” (z_0 = .70) and “Treed” (z_0 = 1.0) (Vickery, Skerlj, et al., 2006). To make use of this framework, we estimate losses based on effective basic gusts (v_b^{effB}), defined as:

$$v_b^{effB} = eW_b v_b^B \qquad \text{Eq.1.5.4}$$

Eq.1.5.4 implies that for a building in a neighborhood configuration that induces eW_b = 1.2, when that neighborhood experiences basic gusts of 45 m/s (100 mph) (v_b^B = 45 m/s) the building would experience the *impact* of basic gusts of 55 m/s (120 mph) (v_b^{effB} = 55 m/s). By logical extension, in such a context, the impact of 55 m/s (120 mph) occurs with the frequency of 45 m/s (100 mph) basic gusts. This latter frequency is derived from a Weibull fitting of basic gusts at the centroid of Census Tracts (Batts et al., 1980).

Because structural response is highly non-linear, the implications of texture-induced changes vary significantly. Considering 45 m/s (100 mph) basic gusts on an unmitigated single-family dwelling in Open terrain, eW_b = 1.2 increases expected losses by 14% of replacement cost; whereas, eW_b = .8 decreases expected losses by only 3% of replacement cost (FEMA 2019).

It is possible to infer eW_b from the relationship between wind loading, wind speed, and drag coefficient. Specifically, wind load is proportional to wind speed (squared) and drag coefficient. Therefore, in the direction of the maximum drag coefficient C_b (discussed prior), we can discuss the effects of texture either in terms of changes to the drag coefficient (shifting from the conventional drag coefficient C_0 to C_b) (for a given v_b^B) or in terms of changes to the wind speeds that load b (shifting from v_b^B to the v_b^{effB} in that direction) (assuming the conventional drag coefficient C_0). That is to say

$$C_b \left(v_b^B\right)^2 = C_0 \left(v_b^{effB,d=4}\right)^2 \qquad \text{Eq.1.5.5}$$

where d is the directional severity of wind loading. To develop the relationship expressed in **Eq.1.5.1**, Roxon repeated CFD simulations for Saffir-Simpson Category 5 winds impinging on the simulated neighborhoods from each of four orthogonal directions (Roxon, 2020). As such, each building had four simulation results (i.e., wind loads and derived drag coefficients) including a maximum drag coefficient C_b and three inferior drag coefficients. For this analysis, Roxon's original simulation results are ranked by d and the ranked set is indexed on $d \in \{1,2,3,4\}$. C_b, as defined in **Eq.1.5.1**, is associated with $d = 4$.

Using **Eq.1.5.5** and the relationship in **Eq.1.5.4**, we infer

$$C_b \left(v_b^B\right)^2 = C_0 \left(eW_b^{d=4} v_b^B\right)^2 \qquad \text{Eq.1.5.6}$$

This provides a relationship between $eW_b^{d=4}$ and C_b. Formally, that is stated as:

$$eW_b^{d=4} = \sqrt{C_b / C_0} \qquad \text{Eq.1.5.7}$$

As discussed prior, each b has a maximum drag coefficient C_b and three inferior drag coefficients. We used these additional simulation results to generate a more complete analysis of building risk. We transformed the simulation results into a dataset of fractions for inferior wind speed ratios $\psi_b^{d\neq 4} = eW_b^d / eW_b^{d=4}$, where $\psi_b^{d\neq 4}$ are modeled as conditional probability functions based on the magnitude of the corresponding observed C_b. Specifically, $\psi_b^{d\neq 4}$ are partitioned into six subsets based on whether the corresponding C_b falls within one of six ranges (as defined in

Table 2.5-1). $\psi_b^{d\neq4}$ within each of the six subsets are fit to a Beta distribution (best fit parameters listed in **Table 2.5-1**). The conditional probability functions are then placed within convolution integrals to evaluate expected losses in each of the inferior directions.

Constructing Building Schemes

Publicly available datasets for building footprints, specifically GIS files, contain limited to no information on occupancy and building type. This lack of information is referred to as under-specification. In this manuscript, under-specification is addressed by probabilistically assigning occupancy and building types to building footprints based on characteristics of the Census Tract in which it is located.

For this analysis, we consider 8 occupancy types, i ($i \in \{RES1, RES2, ..., RES3F\}$ complete list in **Table 2.5-2**), and 27 building types, j ($j \in \{WSF1, WSF2..., MH94HUDIII\}$ complete list can be found in the **Supplementary Materials**). Each building, b, is assigned a likelihood of being each of types ij. The prevalence of occupancy types (e.g., RES1 = single-family dwelling) can be obtained from HAZUS or the U.S. Census Bureau's American Community Survey (ACS). The prevalence of building types can be obtained from probability distributions in HAZUS referred to as building schemes (FEMA n.d.).

Within HAZUS building schemes, each Census Tract belongs to a schematic region (and a state). The distribution of "general" building types is provided on the state level, and the conditional distribution of "specific" building types, given a general building type, is provided on a regional level. General building type defines construction material (e.g., wood-frame), while specific building type further defines construction characteristics (e.g., wood-frame single-family dwelling with one story). HAZUS provides loss functions for each specific building type, and according to whether or not (or which) mitigation measures are applied (listed in **Table 2.5-3**).

Due to data limitations, three assumptions are made about mitigation measures and occupancy types. First, cases considered assume either all or none of the mitigation measures are applied. Future studies could look at the effects of each mitigation measure separately and compare these effects to empirical results from past hurricanes. Second, all building footprints are assumed to be residential (despite the fact that some building footprints are commercial). This should not lead to a significant error, because more than 90% of buildings are residential. Also, we expect commercial buildings to be less susceptible to texture-related loss amplifications, partly because they are built to higher performance standards than residential buildings, and partly because they tend to be found in low density configurations (e.g., strip malls). Lastly, building schemes are assumed to apply uniformly across each Census Tract (though structures of closer proximity are likelier to be similar). To estimate Census Tract totals for losses and benefits, we compute Census Tract averages across all buildings in each Census Tract, and then scale that by only the number of residential buildings.

Estimating the Value of Mitigation

To estimate the value of mitigating against wind-related losses and to quantify the impact of explicitly considering neighborhood texture in that estimate, we evaluate expected losses for individual buildings from four perspectives: With and without mitigation ($m = M$ and $m = \cancel{M}$ respectively), and with and without consideration of local texture ($t = T$ and $t = \cancel{T}$ respectively). More specifically, we define the expected annual benefits (EAB) (of mitigating) for a building b

as the difference between expected annual losses (EAL) when $m = \cancel{M}$ versus $m = M$. Expressed analytically, that is

$$EAB_b^t = EAL_b^{t,\cancel{M}} - EAL_b^{t,M} \quad \text{Eq.1.5.8}$$

Using this metric, it is then possible to evaluate the impact of accounting for texture effects as the change in EAB for b when $t = T$ versus $t = \cancel{T}$. Formally, we define this as the additional expected annual benefits (AEAB) for b, and compute it as:

$$AEAB_b = EAB_b^T - EAB_b^{\cancel{T}} \quad \text{Eq.1.5.9}$$

Referencing our building schemes, EAL for b is a weighted average of EAL estimated for each occupancy type i that b could belong to. EAL for each i is its local replacement cost times the convolution integral of its loss function over the recurrence of effective basic gusts v_b^{effB} acting on b (discussed earlier). Loss functions for each i are weighted averages of curves for each building type j that i could be constructed of, and are also interpolations across curves for characteristic roughness length (based on z_0 of the Census Tract containing b) (Vickery, Skerlj, et al., 2006). EAL is evaluated in each directional severity d, and then averaged (Batts et al., 1980).

Table 2.5-1. Summary of Roxon's simulation results and Beta fitting.

		Range of Maximum Drag Coefficient (C_b)					
		[1.0, 1.5]	(1.5, 2.0]	(2.0, 2.5]	(2.5, 3.0]	(3.0, 3.5]	(3.5, 4.0]
#Observations		77	456	368	300	202	200
eW_b^d	d = 1	.74	.77	.79	.82	.85	.89
		(.02)	(.04)	(.06)	(.08)	(.10)	(.13)
	d = 2	.77	.82	.87	.93	.91	1.03
		(.03)	(.05)	(.07)	(.10)	(.12)	(.16)
	d = 3	.80	.87	.95	1.02	1.10	1.17
		(.03)	(.05)	(.07)	(.10)	(.12)	(.15)
	d = 4	.83	.94	1.06	1.17	1.27	1.37
		(.03)	(.04)	(.03)	(.03)	(.03)	(.03)
eW_b^d / $eW_b^{d=4}$	d = 1	.90	.82	.75	.71	.67	.65
		(.03)	(.05)	(.06)	(.07)	(.08)	(.10)
	$A_x^{d=1}$	73	45	31	26	18	14
	$B_x^{d=1}$	8	10	10	11	9	7
	p-value	.37	.03	<.01	<.01	<.01	.01
	d = 2	.94	.87	.82	.79	.77	.75
		(.03)	(.05)	(.07)	(.08)	(.10)	(.11)
	$A_x^{d=2}$	43	27	19	15	11	9
	$B_x^{d=2}$	3	4	4	4	3	3
	p-value	.69	.07	<.01	.02	.08	.25
	d = 3	.97	.93	.90	.87	.87	.85
		(.03)	(.05)	(.07)	(.08)	(.09)	(.11)
	$A_x^{d=4}$	39	18	12	12	9	7
	$B_x^{d=4}$	1	1	1	2	1	1
	p-value	.98	.09	<.01	.35	.06	.43

Note: means, and standard deviations (in parentheses) across observations; eW_b^d = effective wind speed ratio of observation b for directional severity d ; A_x^d = alpha (shape) parameter; B_x^d = beta (shape) parameter; p-value from Kolmogorov-Smirnov hypothesis testing.

Table 2.5-2. List of occupancy types considered.

Code	Description
RES1	Single-family dwellings
RES2	Manufactured homes
RES3A	Duplexes
RES3B	Triplexes and quads
RES3C	Multi-unit housing with 5-9 units
RES3D	Multi-unit housing with 10-19 units
RES3E	Multi-unit housing with 20-49 units
RES3F	Multi-unit housing with 50+ units

Note: nomenclature for codes borrowed from HAZUS.

Table 2.5-3. List of mitigation measures considered.

Code	Description
MM1	Applying shutters on all windows and entry doors
MM2	Placing straps or clips on roof-to-wall connections
MM3	Providing superior wood roof deck attachment
MM4	Providing superior metal roof deck attachment
MM5	Providing secondary water resistance
MM6	Applying tie downs

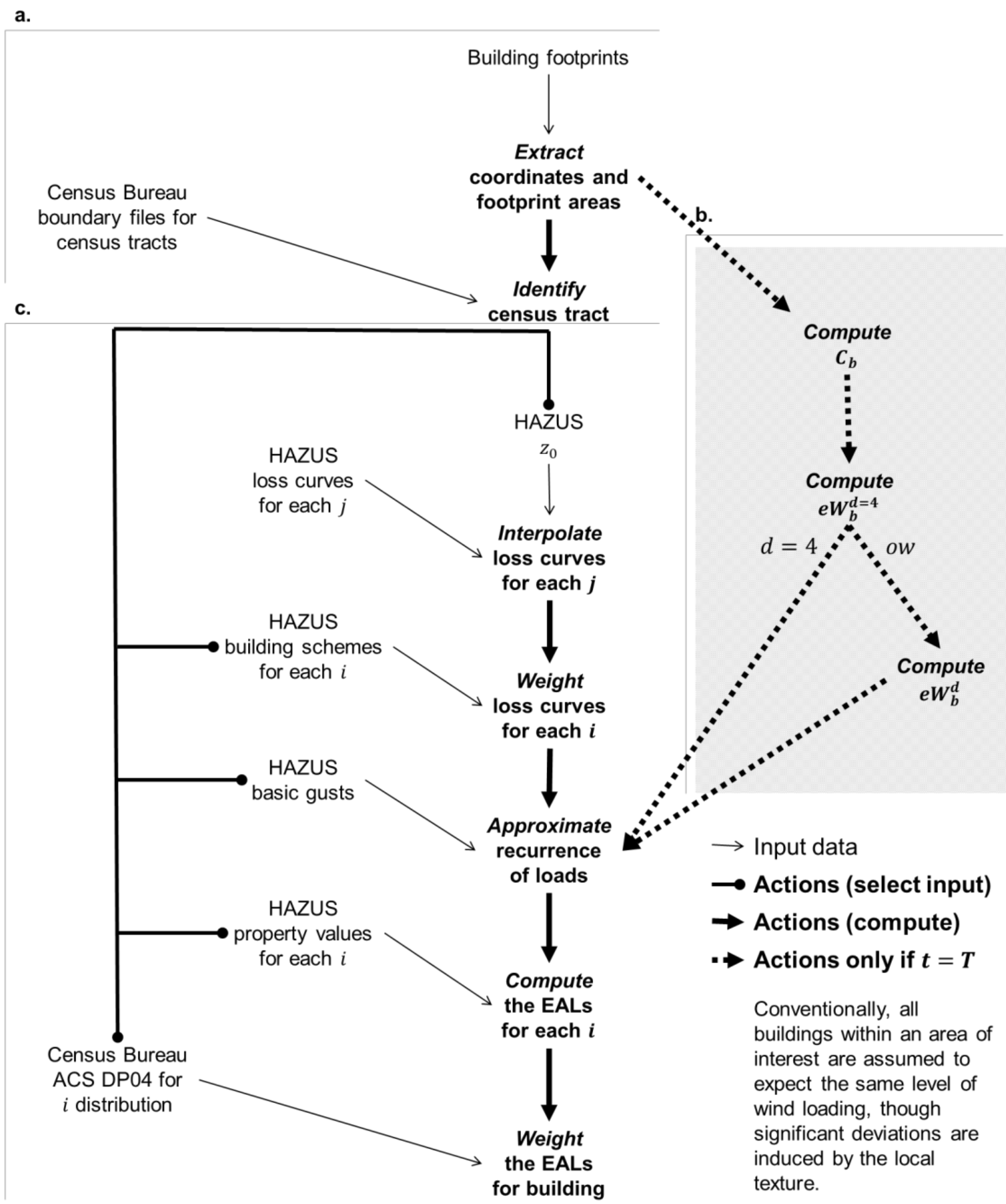

Figure 2.5-1. Methodological flow diagram to compute expected annual losses for building footprints with underspecified occupancy type i and underspecified building type j; **(a)** using GIS files to evaluate local texture; **(b)** incorporating texture into wind loads; C_b = maximum drag coefficient of building b; eW_b^d = effective wind speed ratio of b for directional severity d; (c) constructing building schemes; and, (d) estimating expected losses; z_0 = surface roughness length (m).

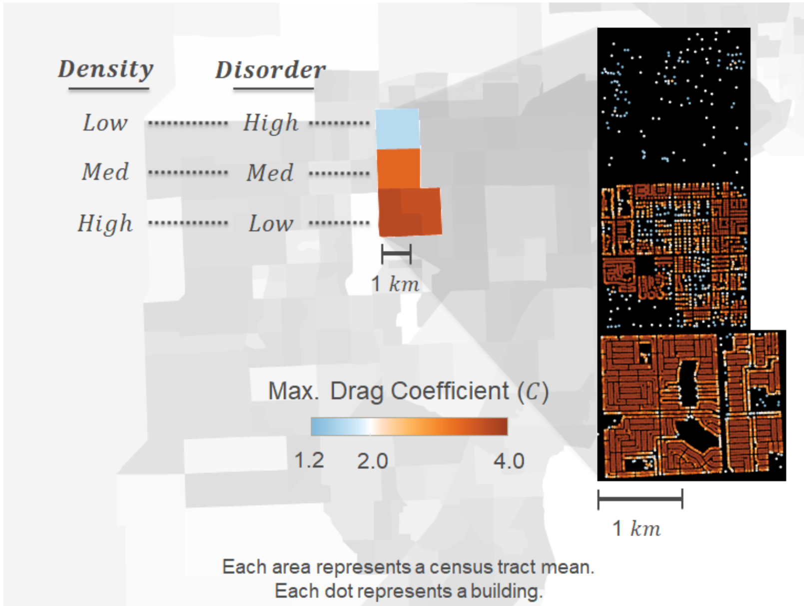

Figure 2.5-2. Trends in local texture across three adjacent Census Tracts; Colors indicate maximum drag coefficient for corresponding building; Greatest load amplifications on buildings in areas with high density/low disorder, and greatest reductions on buildings in areas with low density/high disorder.

2.6 Case Study

To demonstrate the application of our modified, texture-informed framework, we produced a case study on the benefits of mitigating homes in the state of Florida – which currently contains 6.9 million buildings (Microsoft, 2018) and 9.3 million housing units (or households) in 4245 Census Tracts (U.S. Census Bureau, 2020a) (**Table 2.6-1**). In this section, we discuss statewide results along with results for five focal counties. Our focal counties consist of Miami-Dade, Lee, Hillsborough, Orange and Duval county, respectively recognized for the metro areas of Miami, Fort Myers, Tampa, Orlando and Jacksonville. Respectively, they contain 1.0 million, 383 thousand, 564 thousand, 518 thousand and 400 thousand households (U.S. Census Bureau, 2020a) (**Table 2.6-1**). These counties represent a range of exposure to wind-related hazards. As a rule of thumb, more northern counties (like Duval) have less wind exposure than southern ones (like Miami-Dade), and inland counties (like Orange) have less wind exposure than coastal ones (like the other four). Lee and Hillsborough are on the Gulf coast, while Miami-Dade and Duval are on the Atlantic coast (shown in **Figure 2.6-1**).

In our study, all building footprints were extracted from an online repository (Microsoft, 2018). The empirical relationship developed by Roxon requires the attributes of latitude, longitude, and footprint area for each building in a study area. Any dataset that includes these attributes or facilitates their extraction would be sufficient. The online repository we used was systematically derived on national scale. However, various other datasets are available on more localized scales (and their availability is increasing rapidly). Among these datasets, there are those that are prepared by government (e.g., Miami-Dade County's Open Data Hub) (MDC 2019) and those that are crowd-sourced (e.g., OpenStreetMap) (OSM 2021).

Locational attributes were then spatially joined with the U.S. Census Bureau's 2018 cartographic boundary files for assignment of Federal Information Processing Standard (FIPS) codes (U.S. Census Bureau, 2018). Each FIPS code corresponds to a unique Census Tract. Surface roughness length, z_0, recurrence intervals for basic gust wind speeds, v_b^B, and applicable schematic regions were taken from HAZUS. In HAZUS, the surface roughness information was derived from the Florida Water Management Districts (FDEP 2021) and the MRLC Consortium (MRLC Consortium 2015), while the information on recurrence intervals was derived from ASCE 7 wind maps (ASCE 2018). These data sources could be used directly as well. In Florida, there are four HAZUS schematic regions: Southeast (including Miami-Dade), South (including Lee), Central (including Hillsborough and Orange) and North (including Duval).

The HAZUS database also has average replacement costs (for each occupancy type) and loss functions (for each building type). The latest property and loss valuations are in 2018-USD (FEMA 2019). The HAZUS replacement costs were modeled from the RSMeans database (Gordian, 2021) which is the industry standard for labor and materials costs. Future studies could make use of this database in computing costs related to the application of various mitigation measures (Torkian et al., 2014) and comparing these costs to the relevant, texture-informed benefits to evaluate potential homeowner decisions.

Missing information was filled using a nearest-neighbors matrix of centroids of Census Tracts. Of the 4245 Florida Census Tracts, 4207 have z_0 and recurrence intervals available in the HAZUS database; and, 4096 have average replacement cost available in the HAZUS database.

Table 2.6-1. Exposure in Florida and focal counties.

	#Tracts	#Buildings	#Households
Florida	4190	6.90 million	9.25 million
Miami-Dade	518	495 thousand	1.01 million
Lee	166	281 thousand	383 thousand
Hillsborough	319	418 thousand	564 thousand
Orange	206	353 thousand	518 thousand
Duval	173	303 thousand	400 thousand

Note: number of Census Tracts limited to those identified to contain buildings.

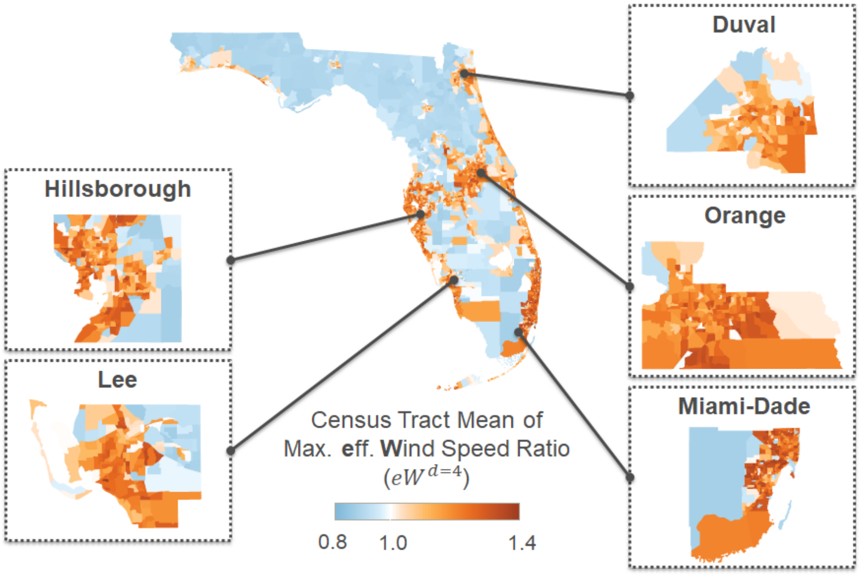

Figure 2.6-1. Map of maximum effective wind speed ratio; Colors indicate Census Tract mean of maximum effective wind speed ratio across Census Tract buildings; Orange indicates potential amplifications in worst-case wind loads, while blue indicates potential reductions in worst-case wind loads.

2.7 Results

Applying the relationships in **Eq.1.5.1** and **Eq.1.5.7**, we estimated the maximum effective wind speed ratio, $eW_b^{d=4}$, for each building in Florida. **Figure 2.6-1** maps the Census Tract level summary of this estimation (in terms of mean of $eW_b^{d=4}$ across buildings in each Census Tract). In **Figure 2.6-1**, orange coloration indicates Census Tracts where, on average, structures experience amplifications in worst-case wind loads, while blue coloration indicates Census Tracts where, on average, structures experience reductions in worst-case wind loads. Each Census Tract represents roughly the same number of households. As such, less dense Census Tracts are cartographically larger and are also associated with potential reductions (blue on the map). Although these encompass a large area on the map, they represent 14% of Florida Census Tracts (and roughly the same fraction of housing units) (**Figure 2.7-1**). Conversely, denser Census Tracts are cartographically smaller and are associated with potential amplifications (orange on the map). They represent 86% of Census Tracts (more than half of which have a mean of $eW_b^{d=4}$ greater than 1.2) (**Figure 2.7-1**). In Florida, these densely built-up areas tend to be along the coastline – where wind-related hazards are already of high concern.

Implications of Texture Effects on Mitigation Benefits

Based on texture-adjusted expected wind loadings, our model results yield expected annual losses (EAL) with a statewide median of $732 per year per household ($/yr/hh) for unmitigated homes ($m = \not{M}$), and $270/yr/hh for mitigated homes ($m = M$) (**Table 2.7-1**). Comparing $m = \not{M}$ versus $m = M$ (as in **Eq.1.5.8**), that yields expected annual benefits (EAB) of mitigating which have a statewide median of $468/yr/hh and reach $1,310/yr/hh to $6,720/yr/hh in the upper quartile of Florida Census Tracts (representing 2.2 million housing units) (**Table 2.7-1**). Comparing analyses considering the impact of texture ($t = T$) to one that does not ($t = \not{T}$), 80% of Census Tracts exhibit an increase in their mean EAB, more than half of which at least double their conventional estimate (**Figure 2.7-2**). Our results yield additional expected annual benefits (AEAB) (as defined in **Eq.1.5.9**) which have a statewide median of \$210/yr/hh and reach \$589/yr/hh to \$3,300/yr/hh in the upper quartile of Census Tracts (**Table 2.7-1**).

Underestimating the value of mitigation can lead to homeowners making sub-optimal decisions about investing in mitigation measures. Among our focal counties, AEAB are lowest in the northernmost, Duval County, and highest in the southernmost, Miami-Dade County. Duval has a mean of \$70/yr/hh with a standard deviation of \$65/yr/hh. Miami-Dade has a mean of \$909/yr/hh with a standard deviation of \$758/yr/hh. And, the other counties average at roughly two hundred dollars per year per household (**Table 2.7-2**).

To better understand what areas are more likely to be associated with underestimated EAB, we explored the correlation between neighborhood characteristics and the magnitude of the underestimate. Specifically, we evaluate the Pearson correlation coefficient between AEAB and several neighborhood characteristics (**Table 2.7-3**, **Table 2.7-4**, and **Table 2.7-5**). AEAB are higher for homes in areas that are more coastal ($\rho = .25$); have more exposure to wind-related hazards (strongly correlated, $\rho = .57$) (**Table 2.7-3**); have higher prevalence of single-family dwellings ($\rho = .33$); and, have lower prevalence of manufactured homes ($\rho = -.29$) (**Table 2.7-4**). Overall, coastal areas tend to be more exposed to wind-related hazards ($\rho = .24$); have lower shielding effects induced by the local terrain ($\rho = -.14$); and, have higher tunneling effects induced by the local texture ($\rho = .27$) (**Table 2.7-5**).

All of our focal counties have suburban/urban terrain (**Table 2.7-3**); have more than 80% of their households living in single-family dwellings; and, have average replacement cost of roughly two hundred thousand dollars per housing unit (**Table 2.7-4**). As they are all densely built-up areas, they are all susceptible to adverse texture effects. However, accounting for these effects scales their EAB at vastly different rates (as discussed earlier). Of them, Miami-Dade, Lee, and Hillsborough (the southernmost counties) are the most coastal (with respectively decreasing wind exposure and AEAB). Duval (the northernmost county) is less coastal (and has low wind exposure, leading to much lower AEAB). And, Orange (relatively more southern) is the least coastal (though has high wind exposure, leading to similar AEAB as Lee and Hillsborough) (**Table 2.7-3**).

Lastly, we computed total expected losses and benefits statewide. Our results show statewide EAL of $12.0 billion per year ($/yr) if all homes are unmitigated, EAL of $3.9 billion/yr if all homes are mitigated, and, therefore, EAB of $8.1 billion/yr. This latter figure includes AEAB of $3.7 billion/yr. This implies that conventional loss estimation models may be underestimating the value of mitigating Florida homes by more than 80%. At present, nearly 40% of single-family dwellings, and manufactured homes, nearly 30% of duplexes, triplexes, and quads, and nearly 20% of larger multi-unit housing include the mitigation measures studied (FEMA 2019) (regional assumptions can be found in the **Supplementary Materials**). Under these assumptions, the state of Florida is currently reaping 47% of potential benefits for mitigating homes against hurricanes. Nevertheless, the state is still exposed to an EAL of $8.2 billion/yr, and there is a remaining $4.3 billion/yr of potential benefits (of which $2.0 billion/yr can be attributed to texture-related loss amplifications).

Table 2.7-1. Summary of expected annual losses and benefits of mitigating ($/yr/hh); Statewide.

	Considering Texture Effects ($t = T$)			
	EAL ($m = \cancel{M}$)	EAL ($m = M$)	EAB	AEAB
Minimum	2	1	1	-1,570
25th percentile	336	139	196	22
50th percentile	732	270	468	210
75th percentile	1,932	608	1,310	589
Maximum	9,470	2,760	6,720	3,300
Mean	1,310	420	885	404
(Std. Deviation)	(1,380)	(400)	(983)	(595)

Note: percentiles, means, and standard deviations across averages for Census Tracts; $m = \cancel{M}$ = unmitigated building stock; $m = M$ = mitigated building stock.

Table 2.7-2. Summary of expected annual losses and benefits of mitigating ($/yr/hh); Focal counties.

	Considering Texture Effects ($t = T$)			
	EAL ($m = \not{M}$)	EAL ($m = M$)	EAB	AEAB
Miami-Dade	2,800	846	1,950	909
	(1,420)	(408)	(1,000)	(758)
Lee	1,220	405	817	230
	(685)	(199)	(498)	(390)
Hillsborough	671	239	432	222
	(406)	(129)	(278)	(212)
Orange	542	219	322	225
	(245)	(93)	(153)	(130)
Duval	226	90	136	70
	(128)	(44)	(84)	(65)

Note: means and standard deviations (in parentheses) across averages for Census Tracts; $m = \not{M}$ = unmitigated building stock; $m = M$ = mitigated building stock.

Table 2.7-3. Summary of explanatory factors; Locational characteristics.

	Coastal-ness	Windiness	Terrain	Texture
Florida	-21	18	.38	1.17 (.18)
Miami-Dade	-10	21	.36	1.24 (.16)
Lee	-7	18	.34	1.12 (.18)
Hillsborough	-11	17	.40	1.16 (.19)
Orange	-57	18	.43	1.21 (.19)
Duval	-21	13	.36	1.14 (.19)
ρ with EAB ($t = \not{T}$)	.42	.71	-.39	.28
ρ with EAB ($t = T$)	.36	.70	-.26	.57
ρ with AEAB	.25	.57	-.12	.70

Note: means and standard deviations (in parentheses) across Census Tracts; Pearson correlation coefficients computed statewide from Census Tract means of EAB, and AEAB; $t = \not{T}$ = not considering texture; $t = T$ = considering texture; Coastal-ness = negative distance of Census Tract centroid from nearest coastline (km); Windiness = Census Tract expected annual basic gust wind speed (m/s); Terrain = Census Tract surface roughness length (m); Texture = Census Tract mean of maximum effective wind speed ratio.

Table 2.7-4. Summary of explanatory factors; Occupancy and building characteristics.

	Single-Family	Manufactured	Multi-Unit	Replacement Cost
Florida	81%	12%	7%	$208,000/hh
Miami-Dade	88%	3%	9%	$218,000/hh
Lee	84%	11%	5%	$246,000/hh
Hillsborough	78%	13%	9%	$196,000/hh
Orange	85%	5%	10%	$253,000/hh
Duval	88%	7%	5%	$246,000/hh
ρ with EAB ($t = \not{T}$)	.30	-.35	.04	.17
ρ with EAB ($t = T$)	.35	-.35	-.04	.19
ρ with AEAB	.33	-.29	-.09	.18

Note: percentages and means across Census Tracts; Pearson correlation coefficients computed statewide from Census Tract means of EAB, and AEAB; $t = \not{T}$ = not considering texture; $t = T$ = considering texture.

Table 2.7-5. Correlation matrix for explanatory factors.

	Coastal.	Wind.	Terrain	Texture	Single-F.	Manuf.	Multi-U.	Repl. C.
Coastal.	1							
Wind.	.24	1						
Terrain	-.14	-.27	1					
Texture	.27	.42	.02	1				
Single-F.	.14	.14	-.16	.28	1			
Manuf.	-.23	-.28	.17	-.28	-.83	1		
Multi-U.	.14	.21	-.00	-.03	-.39	-.20	1	
Repl. C.	-.04	-.01	-.07	.09	.47	-.27	-.39	1

Note: Pearson correlation coefficients computed statewide; Coastal-ness = negative distance of Census Tract centroid from nearest coastline (km); Windiness = Census Tract expected annual basic gust wind speed (m/s); Terrain = Census Tract surface roughness length (m); Texture = Census Tract mean of maximum effective wind speed ratio; Single-family dwellings, manufactured homes, and multi-unit housing in terms of percentages; Replacement cost in terms of $k/hh.

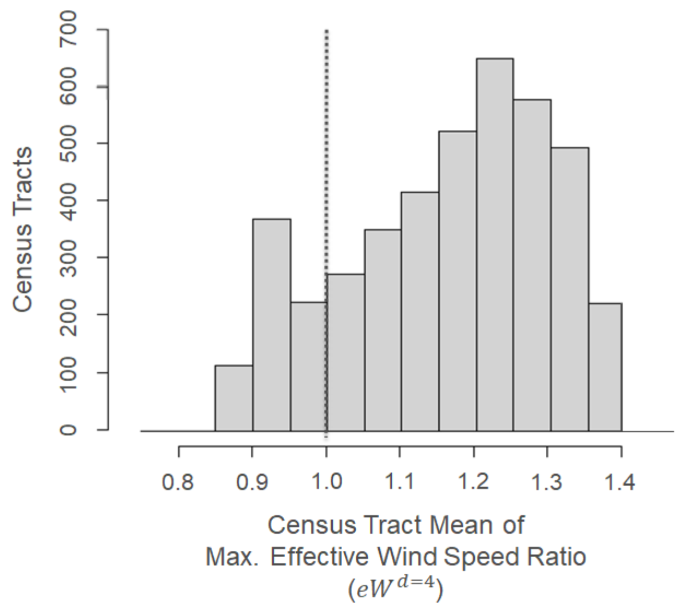

Figure 2.7-1. Histogram of Census Tract mean of maximum effective wind speed ratio; A majority of Florida Census Tracts have potential amplifications in worst-case wind loads.

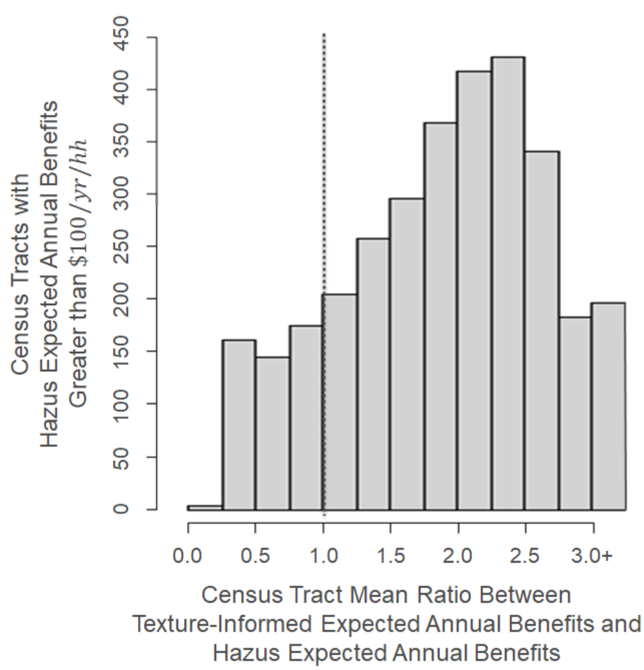

Figure 2.7-2. Histogram of Census Tract mean ratio between texture-informed expected annual benefits and HAZUS expected annual benefits; Filtered to Census Tracts with HAZUS expected annual benefits greater than $100/yr/hh (histogram for Census Tracts with HAZUS expected annual benefits less than $100/yr/hh can be found in the **Supplementary Materials**); A majority of Census Tracts exhibit an increase in expected annual benefits of mitigating homes.

2.8 Discussion

The results of applying our modified framework to a case study on Florida indicate that current loss estimation methods that do not consider texture effects severely underestimate expected losses. Though texture can induce wind loads both higher and lower than conventional estimates, the non-linearity of structural response leads to a significant net increase in expected losses. In total, this increase could be on the order of tens to hundreds of millions of dollars per year on a county level, and on the order of billions of dollars per year on the state level. Our model results suggest that implementing mitigation measures including shutters, straps, and tie downs across unmitigated homes would yield annualized benefits of $4.3 billion statewide ranging from $136 per household in Duval County to $1,950 per household in Miami-Dade County (respectively 100% and 90% higher than conventional estimates) (**Table 2.7-2**).

In current practice, hurricane loss risk is acknowledged to be high along the Atlantic and Gulf coasts – leading to locally stricter building codes in coastal communities (ICC 2017). This study of the implications of neighborhood texture suggests that not only have such risks been previously underestimated, but many communities considered inland and *protected* would benefit significantly from further mitigation. This latter description would be anywhere more than 1.6 km (1 mi) away from the immediate coastline (therefore, including anywhere within Orange County) (ICC 2017). Our findings strongly encourage coastal states to consider broader efforts to adopt strict building codes – especially in densely built-up areas where risk factors compound.

The benefits of mitigating homes extend beyond the magnitude of avoided structural losses captured in the scope of this manuscript. Many other forms of loss accrue to homeowners and communities, including: loss of building contents, debris generation, and business interruption (FEMA 2019). Additionally, mitigation can lead to insurance discounts for homeowners (Malik et al., 2012; The State of Florida, 2011). Finally, as has been widely discussed, many experts believe that storm recurrence intervals may shorten with climate change, but recurrence data available today does not reflect this. All together, these facts signify that the values developed in this study are themselves still underestimates of the value of mitigation. While future studies should expand this work to include such benefits, the values presented here already begin to make a strong case to act now to make buildings more resilient to future storms.

2.9 Data Availability Statement

All data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies. Our study of all hurricane-prone states can be found at: https://cshub.mit.edu/city-texture-dashboard. Our code (with sample input) can be found at: https://github.com/CSHubMIT/texture_loss_estimation. HAZUS software and associated data files can be found at: https://msc.fema.gov/portal/resources/hazus. GIS files for building footprints can be found at: https://github.com/microsoft/USBuildingFootprints. U.S. Census Bureau's cartographic boundary files and ACS data tables can be found at: https://www.census.gov.

2.10 Acknowledgements

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2.11 Declaration of Interest Statement

The authors report there are no competing interests to declare.

2.12 References

References can be found at the end of this work.

3 Contributions to Social Assessment

This chapter includes the manuscript "Priced Out: Measuring the Severe Cost Burden of Hurricane Repairs on Socially-Vulnerable Households" authored by Ipek Bensu Manav and Randolph Kirchain. The title and content of the manuscript may have changed during peer review and publication.

3.1 Abstract

Unlike recovery, which is dictated by hazard events, mitigation is allocated a priori. Mitigation spending could be allocated to either minimize total monetary damage or to minimize the number of households that face severe cost burden. Publicly-available methods for risk assessment lack means to simulate how hazard risks differ across households, hence cannot inform the latter decision.

This manuscript bridges that gap by presenting a scalable, high-resolution method to evaluate expected damages for each individual household. This method is used to develop the first pre-disaster mapping of such across six states tracing the hurricane-prone coasts of the United States. The case study identifies households that face being priced out by hazard repairs, herein referred to as severe cost burden and defined as expected monetary damages in excess of one-quarter of household annual income.

Datasets are created to represent residences and resident households combining physical characteristics and demographics. All analyses use public information from the U.S. Federal Emergency Management Agency (FEMA) and Census Bureau. Across the six states, model

results show 712 thousand households are likely to be severely cost-burdened by hurricane repairs. Socially-vulnerable groups are overrepresented among severely cost-burdened households, including households that are below the poverty line, are single-parent households, belong to minorities, live in mobile homes, and/or include a member with disability. In the case study of Miami-Dade County, FL, a disaster risk reduction policy is characterized to address all avoidable price-out as well as the majority of avoidable monetary damage while selecting only 1% more residences than would be selected if the only criteria were addressing the latter.

3.2 Keywords

Hurricanes, Social Vulnerability, Risk Assessment

3.3 Introduction

An increasing awareness of the tie between climate change and natural hazard events is leading governments to reexamine their spending on disaster risk reduction. Authors across the globe, studying various natural hazards, have shown that investing in pre-disaster mitigation can significantly reduce spending on post-disaster recovery (de Vet et al., 2019; X. Wu & Guo, 2021; Yaron & Wilson, 2020).

Recently, policies in the United States have begun to put this into practice. In the state of Florida alone, more than $100 million in Federal funds have been approved for strengthening new structures and retrofitting existing structures (FEMA 2019a). Maximizing the impact of these funds requires that decision-makers rigorously answer the questions of ‘where’ support is needed and ‘who’ needs it the most.

Across engineering disciplines, vulnerability to natural hazards is commonly represented as deriving from two factors: climate and structures (Pita et al., 2015). Climatological vulnerability relates to living in areas that are prone to natural hazards, while structural vulnerability relates to living in structures that are susceptible to incurring damage. These forms of vulnerability focus on the ‘where’ and ‘what’ dimensions of risk.

A growing body of literature recognizes, however, that the impacts of natural hazards fall disproportionately on disadvantaged communities (Cutter, 2001). This phenomenon has been labeled as social vulnerability. Being socially-vulnerable is defined as lacking the capacity to “anticipate, confront, repair, and recover from the effects of a disaster” (Flanagan et al., 2011). A goal of identifying social vulnerability is identifying the ‘who’ dimension of risk.

Though there are extensive bodies of work on estimating expected damages and on measuring social vulnerability, separately, the literature lacks a quantitative analysis exploring the connection of the former with the latter. The aim of this study is to explore this connection, by using a high-resolution loss estimation approach with probabilistic demographic and socioeconomic models to quantify the heightened risk faced by socially-vulnerable groups.

Our fundamental research questions are: [1] given the current state of modeling and data, could we identify which indicators of social vulnerability correspond to disproportionate risk of being priced out of natural hazard repairs—here we focus on hurricane repairs, [2] how does the present housing stock fare in terms of expected monetary damages and number of households expected to be severely cost-burdened by these damages, and [3] what do these metrics ultimately tell us for disaster risk reduction policy?

3.4 Literature Review

Throughout this manuscript, we refer to three types of vulnerability: climatological, structural, and social. We define climatological vulnerability as living in areas that are prone to natural hazards, structural vulnerability as living in structures that are susceptible to incurring damage during hazard events, and social vulnerability as having demographic or socioeconomic characteristics that increase the likelihood of living in such risky areas and structures as well as lacking the resources to prepare for, respond to, and recover from hazard risks.

Cutter, Boruff, and Shirley (2003) place climatological factors under ‘biophysical’ vulnerability, and structural and social factors under ‘social’ vulnerability. In this work, we modify these definitions to emphasize the type of biophysical risk being discussed and to individually address the risks related to structures and the likelihood of living in them.

There is extensive engineering literature on climatological and structural vulnerability. Here, we focus on the part of that literature that estimates expected wind-related damages. Studies of hurricane losses have examined the risk of loss for various structure components and model structure types (Pita et al., 2015). Regional loss estimation models include: the Hazards U.S. Multi-Hazard (HAZUS-MH) model developed by FEMA (Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006), the Florida Public Hurricane Loss Model (FPHLM) developed by a consortium of Florida universities led by Florida International University (FIU) (Pinelli et al., 2011) and several actuarial models developed by private companies (AIR 2019; ARA 2019; CoreLogic 2019; RMS 2019). Of these, all except for HAZUS are currently proprietary.

Information that is publicly-available suggests that these studies and tools focus on climatological and structural aspects of risk, such as wind exposure, construction materials, and construction types. That is to say: these studies primarily explore the questions of ‘what’ is affected and ‘where’, but largely lack any analysis of ‘who’.

Analysis of ‘who’ is limited to estimates of the number of households that could be displaced or that could require shelter in the event of a hurricane (Rosenheim et al., 2019; Vickery, Skerlj, et al., 2006). These estimates are based only on the extent of structural damage and, hence, do not comment on the variability in demographic and socioeconomic characteristics of affected households. Though these community-level estimates are crucial for disaster planning, overlooking variability in household characteristics discounts disparity in the experiences of at-risk households, and makes it difficult to identify households in most need of mitigation support. As such, HAZUS, and similar tools, can be used to explore risks associated with climatological and structural vulnerability, but are strained in mapping these results to indicators of social vulnerability.

To date, studies of social vulnerability—that are applicable to hurricane-prone areas—have been expansive, spanning various fields and approaches. For the research explored here, we categorize these as studies which develop or report on: [1] social vulnerability indices, [2] vulnerability indices for hurricanes, [3] case studies of hurricane events, and [4] post-disaster surveys of hurricane-impacted households.

There are a number of studies that propose indices to assess the social vulnerability of administrative divisions (e.g., counties, Census Tracts, or Census Block Groups). These indices are based on the unweighted averages of indicators that are referred to as indicators of social vulnerability. These indicators derive from sociological studies, and are used to create generalized indices which include the Social Vulnerability Index (SoVI) developed by Cutter, Boruff, and Shirley (2003) and the Social Vulnerability Index (SVI) developed by the U.S.

Centers for Diseases Control and Prevention (CDC) (Flanagan et al., 2018). Later, expanding on the SoVI, Cutter, Burton, and Emrich (2010) developed a more specialized index for natural disaster resilience.

All of these indices are constructed from Census indicators that either relate to social factors such as demographic and socioeconomic characteristics or serve as proxies for structural damage exposure. The latter are, namely: density of housing permits, density of housing units, density of commercial and manufacturing establishments, and percentage of mobile homes. The natural disaster resilience index introduces structure age as a measure of hazard performance and makes use of the percentage of housing units built before 1970 as proxy. None of these indices include an explicit evaluation of loss risk, nor do they include indicators of climatological vulnerability.

Indices specific to hurricanes include: the Composite Hurricane Vulnerability Index (CHVI) (Prasad, 2013), the Hurricane Vulnerability Index (HVI) (Pompe & Haluska, 2011) and the Hurricane Disaster Risk Index (HDRI) (Davidson & Lambert, 2001). Compared to their more generalized counterparts, these indices incorporate measures of climatological vulnerability to tropical storms (e.g., return period of hurricanes or specific hurricane categories), storm surge (e.g., percentage of land in storm surge inundation zones), and flooding (e.g., percentage of land in flood risk zones).

Similar to their generalized counterparts, however, these indices do not include any explicit evaluation of loss risk, and instead make use of proxies for structural damage exposure. These proxies relate to the density (superscript *d*), value (superscript *v*), and quality (superscript *q*) of the built environment. Namely, these are: percentage of resident and tourist population^{d}, population density^{d}, density of roads^{d}, value of powerlines^{v}, value of properties and farm products^{v}, median value of owner-occupied housing units^{v}, mean structure age^{q}, and mean score from the Building Code Effective Grading Schedule (BECGS) (developed by the Insurance Services Office (ISO))[q].

The studies discussed thus far do not compute expected damages, and instead evaluate loss risk as a linear combination of various indicators. Studies of the response of structures under wind loading show that expected monetary damage is a highly nonlinear combination of the recurrence and intensity of wind loading, the structural and nonstructural characteristics of structures, and the value of structures and contents exposed (Manav et al., 2022).

There are a number of case studies that overlay measures of social, structural, and climatological vulnerability to identify main contributing factors. Case studies focused on coastal hazards include qualitative studies, e.g., that of New Hanover County, SC (Flax et al., 2002), Yaquina Bay, OR (Wood et al., 2002) and Cape May, NJ (S. Wu et al., 2002), and quantitative studies, e.g., that of the State of Rhode Island (Odeh, 2002) and Georgetown, SC (Cutter & Emrich, 2006). Although these case studies do not compute expected damages, some of them deal with post-event estimates of monetary damage. However, these estimates do not give indication of the likelihood of *repeating* an adverse event.

Lastly, there are a number of post-disaster surveys that identify sociological relationships between household characteristics (e.g., minority or tenure status) and household behavior (e.g., decision to dislocate following a hurricane event). Surveys have been conducted for a variety of decisions regarding disaster preparedness, response, and recovery. These surveys include: behavior aggregated on Census Block Group level in Galveston, TX following Hurricane Ike (van Zandt et al., 2012) and behavior aggregated on household level in Southeast Florida following Hurricane Andrew (Peacock et al., 1997).

The latter of these collections of surveys was incorporated into a forward selection logistic regression to build a predictive model of household displacement (Lin, 2009) which was later applied to a case study of a earthquakes in Seaside, OR (Rosenheim et al., 2019). This case study gives insight into how variations in household characteristics can be incorporated into loss estimation. However, this predictive model remains the lone example of an engineering application of social vulnerability information.

Studies of social vulnerability present great potential to capture interdependencies between physical and social systems in hazard-prone communities. However, there remains a disconnect between measuring social vulnerability and estimating expected damages in a context that can be applied to forward-looking engineering questions. This study makes use of Census Public-Use Microdata Sample (PUMS) data to derive such connections and incorporates them into loss estimation. This information is then used to inform the allocation of funds in disaster risk reduction efforts.

3.5 Methodology

The objective of this study is to measure the risk of households being priced out of hurricane repairs and identify indicators of social vulnerability that correspond to heightened risk. Ideally, this would have been accomplished using a single dataset of households, where the demographic and socioeconomic characteristics of each resident and the construction characteristics of their residence are all known. However, in the U.S., the required information is found across several datasets aggregated on various levels at much less granular scales, e.g., Census Block Group, Census Tract, or even Census Division (with decreasing granularity).

To address this, we identify the number of households associated with each geographic location, and use locational context to infer information about residents (e.g., indicators of social vulnerability) and their residences (e.g., occupancy type). We then match up occupancy types with structural and nonstructural characteristics, which enable us to estimate replacement cost and loss functions, both of which are crucial to evaluating expected monetary damage. To do this, our methodology consists of four aspects: [1] iterative proportional fitting of Census data, [2] characterizing the housing stock, [3] simulating resident households and their residences, and [4] evaluating expected loss levels.

To explore the dimensions of vulnerability to hurricanes, we compute household risk exposure from three perspectives: [1] absolute-dollar (AD) losses (a dollar value of expected monetary damage), [2] per-replacement-cost (PRC) losses (a percentage metric of the extent of expected monetary damage), [3] per-annual-income (PAI) losses (a percentage metric of the cost burden of expected monetary damage, or the affordability of hurricane repairs).

For this, we use the CDC's SVI and various surveys from the U.S. Census Bureau in an augmented HAZUS methodology (Manav et al., 2022). The SVI is used to identify household characteristics that are pertinent to social vulnerability. Census data enables us to map household and housing characteristics to specific locations (and, therefore, to climatological and structural risk). Our framework allows us to estimate wind-related loads and losses for each residence. Together, this framework and data simulate how hurricane risk exposure varies across demographics. The results of this inquiry reveal how prioritizing one of the loss metrics shapes disaster risk reduction policy.

Iterative Proportional Fitting of Census Data

The CDC's SVI includes 15 indicators of social vulnerability (listed in **Table 3.5-1**) (Flanagan et al., 2018). Of these indicators, 14 are considered in this study. 12 are included in characteristics of households, and 2 are included in characteristics of their housing. SVI3 ('Mean income') is replaced by household annual income and modeled by income brackets. SVI11 ('Multi-unit structures') and SVI12 ('Mobile homes') are incorporated into model occupancy types. SVI15 ('Group quarters') is excluded because it is not covered by these occupancy types.

In this study, 10 income brackets (IBs) are considered (listed in **Table 3.5-2**). Each income bracket is assigned a midrange household annual income, e.g., IB2 ('Between $10,000 to 14,999/yr') is assigned $12,500 / year. Also, 8 residential occupancy types are considered (listed in **Table 3.5-3**).

Our iterative proportional fitting (IPF) is comprised of two steps. First, Census PUMS data is used to derive state-level, general joint distribution tables. There are 12 such general joint distribution tables: [1] income bracket v. occupancy type, [2-12] income bracket v. social vulnerability indicator. Formally, that is

$$P_{ij}^{0} = N_{ij} / N \qquad \text{Eq.2.5.1}$$

where N = number of entries in PUMS data, N_{ij} = number of entries that both are of income bracket i and have characteristic j (e.g., occupancy type or social vulnerability indicator), P_{ij}^{0} = percent value of the same. The superscript 0 indicates the 0^{th} iteration.

Then, data tables are used to fit these general joint distribution tables to joint distributions specific to location (e.g., in this study, Census Tract). This data includes: [1] percent distribution of income brackets, represented by P_i, [2] percent distribution of occupancy types, represented by P_j, [3-13] percent prevalence of each social vulnerability indicator not covered by income brackets and occupancy types, also represented by P_j.

A total of 1+11 such specific joint distribution tables (referred to later as IPF tables) are derived. In IPF, rows and columns are scaled iteratively until each row adds up to the location-specific percent distribution of each income bracket, that is

$$P_{ij}^{t'} = P_{ij}^{t'-1} * P_i / \sum_j P_{ij}^{t'-1},\ i = 1, 2, ... \qquad \text{Eq.2.5.2}$$

where $P_{ij}^{t'}$ = percent of households that both are of income bracket i and have characteristic j after row operations for iteration $t' = 1, 2, ...$. Each column adds up to the location-specific percent distribution of each characteristic of interest (e.g., occupancy type or social vulnerability indicator), that is

$$P_{ij}^{t} = P_{ij}^{t-1} * P_j / \sum_i P_{ij}^{t-1},\ j = 1, 2, ... \qquad \text{Eq.2.5.3}$$

where P_{ij}^{t} = percent of households that both are of income bracket i and have characteristic j after column operations for iteration $t = 1, 2, \ldots$. And, also, the entire table adds up to 1±.1%. Specifically,

$$\sum_i \sum_j P_{ij}^{\tau} = 1 \qquad \text{Eq.2.5.4}$$

where P_{ij}^{τ} = percent of households that both are of income bracket i and have characteristic j after last iteration τ.

Throughout this study, we make use of data from the U.S. Census Bureau and CDC. The American Community Survey (ACS) provides state-level PUMS data (U.S. Census Bureau, n.d.-a). The ACS DP03 (Selected Economic Characteristics) includes Census-Tract-level distribution of income brackets, and the ACS DP04 (Selected Housing Characteristics) includes Census-Tract-level distribution of occupancy types.

The CDC's database includes Census-Tract-level distribution of social vulnerability indicators (CDC and ATSDR n.d.). However, if necessary, this data could also be found from the U.S. Census Bureau (except, different indicators might fall in the scope of different surveys, e.g. DP03 and DP04 mentioned above).

Characterizing the Housing Stock

To compute expected damages, we need information about the housing stock, namely replacement costs and loss functions, the latter of which describes expected levels of loss at each event intensity (e.g., peak gust wind speed) as a percentage of replacement cost.

In HAZUS, each occupancy type corresponds to a replacement cost. Formally, that is

$$RC = C * SF \quad \text{Eq.2.5.5}$$

where RC = replacement cost for a given occupancy type (\$), C = unit cost per square foot (\$ / sqft) (a function of Census Division, income ratio, and occupancy type), SF = square footage (sqft) (a function of Census Division and income ratio) (FEMA 2021b). In HAZUS, income ratio (IR) refers to the ratio between Census Block Group median income and Census Division median income. IRs represent cost fluctuations associated with different locations. To calculate IRs, we made use of ACS data (U.S. Census Bureau, n.d.-a).

Additionally, replacement cost for RES1 (‘Single-family dwellings’) includes the cost of basement and garage. That is

$$RC' = C' * SF + \chi_b * SF + \chi_g \quad \text{Eq.2.5.6}$$

where RC' = replacement cost for RES1 (\$), C' = unit cost per square foot (\$ / sqft) (a function of Census Division, IR, number of stories, and presence of basement), χ_b = basement unit cost per square foot (\$ / sqft) (a function of Census Division, IR, number of stories, and finishing of basement), χ_g = garage unit cost (\$) (a function of IR and size of garage) (FEMA 2021b).

To assess the prevalence and characteristics of basements and garages, we made use of American Housing Survey (AHS) (U.S. Census Bureau, 2019) and Survey of Construction (SoC) (U.S. Census Bureau, 2020c) PUMS data pertaining to single-family dwellings.

In this study, the distribution of number of stories, ϕ_S, is modeled as

$$\phi_S = P(S = s \mid IB) \quad \text{Eq.2.5.7}$$

where S = number of stories (a function of Census Division and income bracket based on AHS PUMS data).

The distribution of framing materials, ϕ_F, is modeled as

$$\phi_F = P(F = f \mid S) \qquad \text{Eq.2.5.8}$$

where F = framing material is (a function of Census Division and number of stories based on SoC PUMS data, $F \in$ {wood-frame, concrete block, and concrete}). Knowing a residence's framing material, we can assign it a HAZUS general building type (GBT), e.g. W = wood, M = masonry (or concrete block), and C = concrete (FEMA 2021b). Further knowing a residence's number of stories, we can assign it a HAZUS specific building type (SBT), e.g. WSF1 = wood single-family dwelling with one story (FEMA 2021b),

The prevalence and characteristics of basement, ϕ_B, are modeled as

$$\phi_B = P(B = b \mid S, F) \qquad \text{Eq.2.5.9}$$

where B = presence and finishing of basement (a function of Census Division, number of stories and framing material based on SoC PUMS data).

Similarly, the prevalence and characteristics of garage, ϕ_G are modeled as

$$\phi_G = P(G = g \mid S, F) \qquad \text{Eq.2.5.10}$$

where G = presence and size of garage (a function of Census Division, number of stories and framing material based on SoC PUMS data).

At the level of detail of SBTs, we can assign each residence a loss function (FEMA 2021a). As discussed prior, the prevalence of SBTs for single-family dwellings derives from the AHS and SoC, the latter of which includes information on framing material. Since the SoC is not available for multi-unit housing, the prevalence of SBTs for multi-unit housing is based on regional assumptions in HAZUS (FEMA 2019b).

HAZUS loss functions also incorporate information on terrain (i.e., density of surrounding structures and vegetation) and wind building characteristics (WBCs) (e.g., roof type, roof cover type, roof deck attachment,…) (FEMA 2021a). In the HAZUS database, surface roughness length (for terrain) can be found for each Census Tract, and the prevalence of each WBC is based on regional assumptions (FEMA 2019b). HAZUS regions are not to be confused with Census Regions, which can represent very different scales. For instance, the Southeast Florida HAZUS region spans only Miami-Dade, Broward, and Palm Beach counties, while the South Census Region spans these counties as well entire and multiple states.

Simulating Resident Households and Their Residences

The ACS provides data on the number of households present in each Census Block Group (U.S. Census Bureau, n.d.-a). As outlined in the previous section, we sample from the 12 IPF tables to attribute each household an income bracket (sampled from $\{1,2,\ldots,10\}$ based on the location-specific distribution of income brackets), occupancy type (sampled from $\{1,2,\ldots,8\}$ based on the location-specific joint distribution of occupancy types and income brackets), and social vulnerability indicators (sampled from $\{0,1\}$ based on the location-specific joint distribution of social vulnerability indicators and income brackets). Then, we further attribute each household a set of housing characteristics (i.e., replacement cost and loss function). Thus, we obtain a simulated dataset of households in an area of interest where all necessary information is known to evaluate expected damages.

Evaluating Expected Loss Levels

In **Chapter 2** of this work, we show that the HAZUS loss estimation methodology tends to underestimate expected wind loads and damages by assuming all structures within a given Census Tract and of a given occupancy type experience the same level of expected monetary damage (Manav et al., 2022). This methodology is augmented using an empirical relationship that takes information on the density and arrangement of surrounding structures, referred to as neighborhood texture, to estimate structure-specific wind loading variations. (Textural information readily derives from publicly-available shapefiles of building footprints.)

In this chapter, we implement this empirical relationship and simulate building-specific wind loading, expressed as an effective wind speed ratio, to account for texture effects. Since these ratios are computed for each building footprint, in Census Block Groups with multi-unit housing, the number of households may be greater than the number of unique ratios, in which case multiple households are attributed the same building footprint and effective wind speed ratio.

Using this augmented approach, expected annual losses (EALs) are derived from an effective wind speed ratio, local recurrence of wind speeds, and expected monetary damage at each wind speed (i.e., loss function) (Manav et al., 2022). Recurrence information, as well as loss functions, can be found in the HAZUS database (FEMA 2019b).

In the following sections, we refer to three EAL metrics: [1] absolute-dollar (AD), [2] per-replacement-cost (PRC), [3] per-annual-income (PAI). AD losses represent annual dollar values. Formally, that is

$$AD = RC * \sum_{w} E[MD \mid w] * P(w) \qquad \text{Eq.2.5.11}$$

where RC = replacement cost ($), $E[MD \mid w]$ = expected value of monetary damage at effective wind speed w, $P(w)$ = annual probability of recurrence of effective wind speed w. Here, this effective wind speed distribution is unique to each building footprint (incorporating both its effective wind speed ratios and the local recurrence of wind speeds in its Census Tract).

PRC losses normalize AD losses by replacement cost, that is

$$PRC = AD / RC \qquad \text{Eq.2.5.12}$$

and PAI losses normalize AD losses by household annual income, that is

$$PAI = AD / AI \qquad \text{Eq.2.5.13}$$

where AI = household annual income ($ / year).

The EAL metrics can be interpreted as the value (**Eq.2.5.11**), extent (**Eq.2.5.12**), and cost burden (**Eq.2.5.13**) of expected monetary damage. Having three metrics allows us to explore the impacts of hurricane damages from multiple perspectives.

Table 3.5-1. List of social vulnerability indicators included in the CDC's Social Vulnerability Index.

Code	Description
SVI1	Below poverty
SVI2	Unemployed
SVI3	Mean income
SVI4	No high school diploma
SVI5	Aged 65yo or older
SVI6	Aged 17yo or younger
SVI7	With disability
SVI8	Single-parent household
SVI9	Minority
SVI10	English less than "well"
SVI11	Multi-unit structures
SVI12	Mobile homes
SVI13	Crowding
SVI14	No vehicles
SVI15	Group quarters (not modeled)

Note: SVI3 ('Mean income') covered by income brackets; SVI11 ('Multi-unit structures') and SVI12 ('Mobile homes') covered by occupancy types.

Table 3.5-2. List of income brackets considered.

Code	Description
IB1	Up to $9,999/yr
IB2	Between $10,000 to 14,999/yr
IB3	Between $15,000 to 24,999/yr
IB4	Between $25,000 to 34,999/yr
IB5	Between $35,000 to 49,999/yr
IB6	Between $50,000 to 74,999/yr
IB7	Between $75,000 to 99,999/yr
IB8	Between $100,000 to 149,999/yr
IB9	Between $150,000 to 199,999/yr
IB10	More than $200,000/yr

Table 3.5-3. List of occupancy types considered.

Code	Description
RES1	Single-family dwellings
RES2	Manufactured residences
RES3A	Duplexes
RES3B	Triplexes and quads
RES3C	Multi-unit housing with 5-9 units
RES3D	Multi-unit housing with 10-19 units
RES3E	Multi-unit housing with 20-49 units
RES3F	Multi-unit housing with 50+ units

Note: nomenclature for codes borrowed from HAZUS.

3.6 Case Study

To explore the relationship between social vulnerability and hurricane risk exposure, we apply the methodology described in **Section 3.5** to analyze all residences within the states along the hurricane-prone Gulf Coast, including the states of Florida, Georgia, Alabama, Mississippi, Louisiana, and Texas. In total, this represents analyzing loss risk for more than 13 million structures and 25 million households. In the body of this manuscript, we present a detailed look at the results for the county of Miami-Dade, FL, and then summarize the results for the six states. Detailed state results can be found in the **Supplementary Materials**.

Miami-Dade County, Florida

The analysis of Miami-Dade County, FL is based on a simulation of 937,657 households, information about which were compiled from data and shapefiles from 781 Census Tracts (U.S. Census Bureau, 2020a), 3,736 Census Block Groups (U.S. Census Bureau, 2020a), and more than 300,000 building footprints (Microsoft, 2018). For consistency, all datasets and shapefiles pertain to 2018 and all dollar values are in 2018-USD.

Of these households, 65% live in single-family dwellings, 5% in mobile homes, and the rest in multi-unit housing (**Table 3.6-1**). Of households living in multi-unit housing, 34% live in low- to mid-rise structures, and 66% in mid- to high-rise structures (**Table 3.6-1**). In this case study, occupancy types RES3A-C are grouped together to represent low- to mid-rise multi-unit housing, and RES3D-F are grouped to represent mid- to high-rise multi-unit housing. This aligns with CDC's definition of SVI11 ('Multi-unit structures') which encompasses RES3D-F. This also captures the difference in structural behavior between low- to mid-rise structures and mid- to high-rise structures.

Table 3.6-1 presents the intermediary results of IPF to estimate the median income and percent prevalence of social vulnerability indicators, for the county in aggregate as well as broken down by occupancy type. Median income for households in single-family dwellings ($87,500/yr) is above the county median ($62,500/yr). Correspondingly, median income for households in mobile homes and multi-unit housing fall below the county median. Indicators of social vulnerability show an inverse relationship with household annual income (at varying degrees), hence socially-vulnerable groups are comparatively more prominent in mobile homes and multi-unit housing, particularly in low- to mid-rise multi-unit housing. For instance, 12-13% of households in the occupancy types are estimated to be single-parent households, while a lower 9% of households in single-family dwellings are estimated as such.

Exploring expected annual losses (EALs), **Table 3.6-2** presents the county median for each EAL metric, as well as the same broken down by occupancy type and by socially-vulnerable group. Median EALs are $2,269 / year / household (or 1% of replacement cost, or 4% of annual income). Median EAL ranges as high as $10,338 / year / household (or 25% of replacement cost, or 41% of annual income) for mobile homes, and as low as $1,155 / year / household (or 1% of replacement cost, or 4% of annual income) for low- to mid-rise multi-unit housing. The lowest per-annual-income (PAI) losses are in single-family dwellings and mid- to high-rise multi-unit housing (at 4% of annual income), where households are relatively higher-income.

Additionally, the three EAL metrics are rank-correlated (**Table 3.6-3**). We used Spearman rank correlation for continuous v. continuous variables (e.g., EALs v. household annual income), and Kruskal-Wallis rank sum testing for continuous v. categorical variables (e.g., EALs v. social vulnerability indicators). Spearman rank correlation indicates that household annual income is strongly negatively-correlated with per-annual-income (PAI) losses ($\rho = -.44$) (which may be expected as this metric derives from household annual income), slightly positively-correlated with absolute-dollar (AD) losses ($\rho = .12$), and very slightly positively-correlated with per-replacement-cost (PRC) losses ($\rho = .04$) (**Table 3.6-3**). This suggests that monetary damage may be driven by replacement costs being higher in higher-income communities, which in turn may be offset by the availability of financial resources in these communities to respond to hurricane repair needs.

Kruskal-Wallis rejects the null hypothesis that EALs are similarly distributed for socially-vulnerable and non-socially-vulnerable groups at < .001 statistical significance for most pairs of groups (**Table 3.6-2**). This suggests that loss risk falls disproportionately on socially-vulnerable groups.

Table 3.6-1. Percent prevalence of each group; households.

Description	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	923,957	603,548	50,470	93,020	176,919
Median income ($/yr)	62,500	87,500	20,000	20,000	42,500
Below poverty (%)	20	15	33	36	26
Unemployed (%)	6	5	8	8	7
No high school diploma (%)	16	15	20	19	16
Aged 65yo or older (%)	16	15	19	18	17
Aged 17yo or younger (%)	19	19	20	20	19
With disability (%)	10	9	13	14	11
Single-parent household (%)	10	9	13	12	10
Minority (%)	79	77	84	84	78
English less than "well" (%)	18	17	24	24	19
Multi-unit structures (%)	19	-	-	-	100
Mobile homes (%)	5	-	100	-	-
Crowding (%)	5	5	6	6	5
No vehicles (%)	12	14	8	8	10

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 3.6-2. Expected annual loss (EAL) metrics; median.

	AD	PRC	PAI
Population	$2,269	1%	4%
RES1	$2,513	1%	4%
RES2	$10,338	25%	41%
RES3A-C	$1,155	1%	5%
RES3D-F	$1,877	1%	4%
Below poverty	$1,963*	1%*	20%*
Unemployed	$2,014*	1%*	8%*
No high school diploma	$2,005*	1%*	5%*
Aged 65yo or older	$2,308*	1%*	5%*
Aged 17yo or younger	$2,312	1%*	4%*
With disability	$2,162*	1%*	7%*
Single-parent household	$2,134*	1%*	7%*
Minority	$2,289*	1%*	4%*
English less than "well"	$2,188*	1%*	7%*
Multi-unit structures	$1,877*	1%***	4%*
Mobile homes	$10,338*	25%*	46%*
Crowding	$1,948*	1%*	5%*
No vehicles	$1,839**	1%*	2%*

Note: Kruskal-Wallis rank sum testing rejects the null hypothesis that EALs are similarly distributed for socially-vulnerable and non-socially-vulnerable groups at *< .001 statistical significance for most pairs of groups; **< .01, ***< .05; AD = absolute-dollar EALs ($ / year / household), PRC = per-replacement-cost EALs (% / year / household), PAI = per-annual-income EALs (% / year / household); RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 3.6-3. Correlation of expected annual loss (EAL) metrics; Spearman correlation coefficient.

	AD	PRC	PAI
AD	1		
PRC	.56	1	
PAI	.75	.30	1
Household income	.12	.04	-.44

Note: AD = absolute-dollar EALs ($ / year / household), PRC = per-replacement-cost EALs (% / year / household), PAI = per-annual-income EALs (% / year / household).

3.7 Results

The objective of this study is to observe to what extent indicators of socially vulnerability correspond to heightened risk of being priced out of hurricane repairs, and present how financially challenging levels of monetary damage could be prevented through data-informed disaster risk reduction policy. Our results consist of three parts: [1] identifying households likely to be priced out of repairs, [2] measuring expected performance of the housing stock, and [3] prioritizing residences for further retrofitting.

Identifying Households Likely to Be Priced Out of Repairs

We found that 88,364 households are at risk of being priced out of hurricane repairs (**Table 3.7-1**). In this study, we refer to such households as severely cost-burdened and assume that the threshold for being severely cost-burdened is expecting levels of monetary damage which, on average, exceed three months of household income (or one-quarter of household annual income). However, in reality, this threshold might be much lower. According to a recent survey, half of Americans have less than three months of income in an emergency fund, and this includes one-quarter of Americans that have no emergency fund at all (Bankrate, 2021).

Table 3.7-1 presents the median income and percent prevalence of social vulnerability indicators for households identified as severely cost-burdened by hurricane repairs. Median income is below the county median for severely cost-burdened households and most of the socially-vulnerable groups are overrepresented among these households.

Chi-squared testing rejects the null hypothesis that socially-vulnerable groups are proportionately represented among severely cost-burdened households at < .001 statistical significance for all groups (**Table 3.7-1**). For example, if households with incomes below the poverty line were represented proportionately, we would expect 88,364 x 20% = 17,673 impoverished households to be severely cost-burdened by hurricane repairs. However, our model results yield 88,364 x 71% = 62,738 such households. Similarly, we would expect 88,364 x 10% = 8,836 single-parent households to be severely cost-burdened, but our model results yield a higher number of 88,364 x 15% = 13,254 such households.

Figure 3.7-1 shows ratios between percent prevalence of socially-vulnerable groups among severely cost-burdened households and their overall percent prevalence, e.g., 71% / 20% = 3.6 for impoverished households (see **Supplementary Materials** for derivation). A ratio of 1 implies that a group is proportionately represented among severely cost-burdened households. A ratio greater than 1 implies that a group is overrepresented, where the greater the ratio the greater the overrepresentation, or disparity. From these ratios, we observe that all socially-vulnerable groups are overrepresented among severely cost-burdened households (with the exception of two groups discussed in the next paragraph). This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members who have disability, that speak English less than “well”, and/or that live in mobile homes.

Exceptionally, SVI11 (‘Multi-unit structures’) and SVI14 (‘No vehicles’), both of which fall under the Housing and Transportation domain of the CDC’s SVI (Flanagan et al., 2018), are underrepresented (not overrepresented) among severely cost-burdened households. These characteristics relate to living in densely built-up areas, where vulnerability of the built environment is driven by insufficiency or inefficiency of evacuation routes, rather than damage in structures (what is simulated in this study). These areas comprise mostly mid- to high-rise multi-unit housing, which have better hazard performance than single-family dwellings and mobile homes.

Comparing Miami-Dade to the entire state of Florida, the overrepresentation of minority households is more pronounced in the state results. The ratios for SVI9 (‘Minority’) and SVI10 (‘English less than “well”’) are visibly greater in the state results (**Figure 3.7-1**). Some studies caution against using these characteristics as indicators of social vulnerability in Miami-Dade, because of its unique composition, with several neighborhoods that are majority Hispanic, particularly Cuban, and conduct their local affairs in Spanish (Peacock et al., 1997). This allows for households that speak English poorly, or even not at all, to access resources for preparedness and response as easily as their counterparts who are white and/or speak English fluently.

Furthermore, comparing Florida to the other five states, similar socially-vulnerable groups tend to be overrepresented among severely cost-burdened households. In all states, ratios greater than 1.5 include indicators SVI1 (‘Below poverty’), SVI2 (‘Unemployed’), SVI7 (‘With disability’), SVI8 (‘Single-parent household’), and SVI12 (‘Mobile homes’). Additionally, some states include other indicators associated with socioeconomic status, e.g. SVI4 (‘No high school diploma’) (in Georgia, Louisiana, and Texas), and minority status, e.g. SVI9 (‘Minority’) (in Alabama and Louisiana) and SVI10 (‘English less than “well”’) (in Florida, Louisiana, and Texas).

Table 3.7-1. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households.

Description	Population	Cost-Burdened
Total (#)	923,957	88,364
Median income ($/yr)	62,500	5,000
Below poverty (%)	20	71
Unemployed (%)	6	11
No high school diploma (%)	16	22
Aged 65yo or older (%)	16	19
Aged 17yo or younger (%)	19	21
With disability (%)	10	16
Single-parent household (%)	10	15
Minority (%)	79	88
English less than “well” (%)	18	30
Multi-unit structures (%)	19	17
Mobile homes (%)	5	14
Crowding (%)	5	6
No vehicles (%)	12	2

Note: Chi-squared testing rejects the null hypothesis that socially-vulnerable groups are proportionately represented among severely cost-burdened households at < .001 statistical significance for all groups.

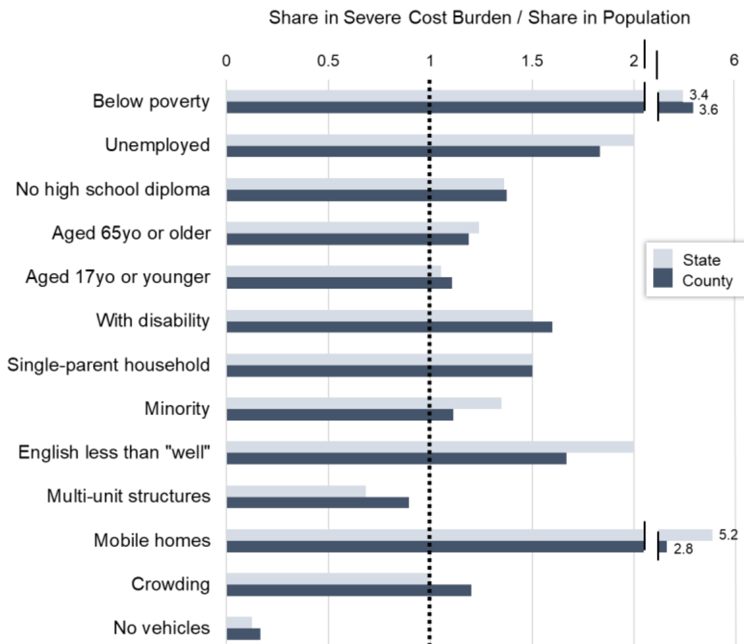

Figure 3.7-1. Ratio between percent prevalence of each group among severely cost-burdened households and their overall percent prevalence for State of Florida (in light blue) and for county of Miami-Dade, FL (in dark blue); disparity is highest for households that are below the poverty line, that have members who are unemployed, that have members who have disability, that speak English less than “well”, and/or that live in mobile homes.

Measuring Expected Performance of the Housing Stock

In this study, 8 mitigation measures are considered (listed in **Table 3.7-2**). There are several other structural and nonstructural factors that contribute to hazard performance. However, decisions relating to many of these factors are only applicable for new structures (e.g., selection of framing materials). Mitigation measures considered here can be applied to both new and existing structures (e.g., as a part of retrofitting).

Figure 3.7-2 shows the number of households severely cost-burdened by monetary damage. In the two extremes, the number of households severely cost-burdened by hurricane repairs would be 122,600 / year if no mitigation measure were applied, and 52,562 / year if all of the mitigation measures were applied. So, 70,038 households / year could be removed from severe cost burden through using these mitigation measures. We can call this avoidable price-out. Our model results indicate that 51% of avoidable price-out currently remains in the county (calculated from the current estimate of 88,364 households / year expecting severe cost burden, as (88,364 - 52,562) / (122,600 - 52,562) = 51%). (The remaining avoidable price-out ranges between 54-67% for the five states.)

Figure 3.7-3 shows the total expected monetary damage. In the two extremes, the value of monetary damage would be $3.33 billion / year if no mitigation measures were applied, and $1.55 billion / year if all of the mitigation measures were applied. So, $1.78 billion / year of monetary damage could be prevented through using these mitigation measures. Our model results indicate that 46% of avoidable monetary damage currently remains in the county (calculated from the current estimate of $2.37 billion / year of expected monetary damages, as

(2.37 - 1.55) / (3.33 - 1.55) = 46%). (The remaining avoidable monetary damage ranges between 51-70% for the five states.)

In **Figure 3.7-2** and **Figure 3.7-3**, there exists a level of monetary damage as well as a number of households severely cost-burdened by this damage even in the ‘fully mitigated’ case. This should not be interpreted as risk that is inevitable, but rather risk that requires more strenuous measures to be taken than the mitigation measures listed in **Table 3.7-2**, such as adoption and enforcement of stricter structure codes.

In the following section, we will focus on the portion of risk reduction that is achievable using only the mitigation measures listed in **Table 3.7-2**. We offer two possible schemes for prioritizing residences in a regional effort. One prioritizes residences by cost burden (ranking households based on their per-annual-income (PAI) losses) (**Figure 3.7-4**), and the other prioritizes residences by monetary damage (ranking households based on their absolute-dollar (AD) losses) (**Figure 3.7-5**).

Table 3.7-2. List of mitigation measures considered.

Code	Description
MM1	Applying shutters on all windows and entry doors
MM2	Placing straps or clips on roof-to-wall connections
MM3	Providing superior wood roof deck attachment
MM4	Providing superior metal roof deck attachment
MM5	Providing secondary water resistance
MM6	Applying tie downs

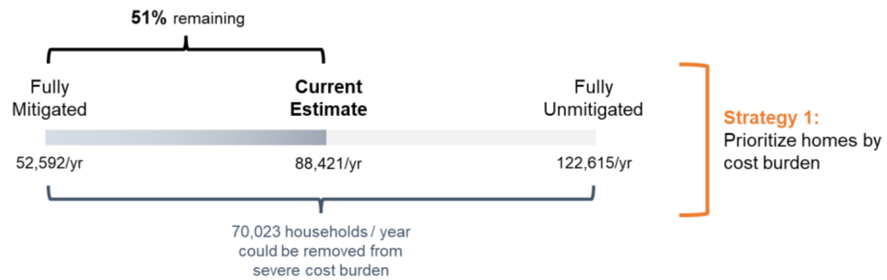

Figure 3.7-2. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year.

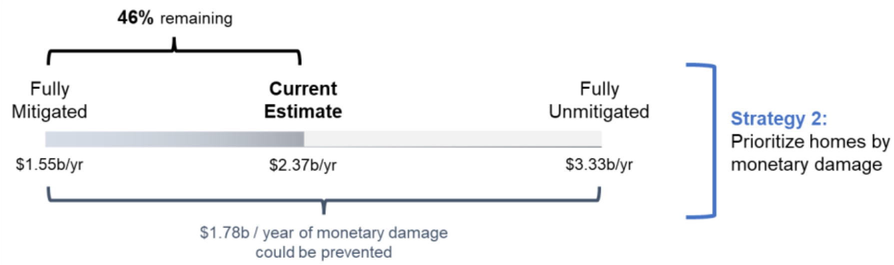

Figure 3.7-3. Total expected monetary damage by mitigation level; $ billion / year.

Prioritizing Homes for Further Retrofitting

We found that the current estimate of avoidable monetary damage and price-out that remains in Miami-Dade corresponds to roughly 25% of residences having all of the mitigation measures listed in **Table 3.7-2** (or 75% having none of them). With that, we can discuss the possible outcomes of further retrofitting under two prioritization schemes: either ranking households based on their PAI losses ('Strategy 1' in **Figure 3.7-2**, **Figure 3.7-4**, and **Figure 3.7-5**) or ranking them based on their AD losses ('Strategy 2' in **Figure 3.7-3**, **Figure 3.7-4**, and **Figure 3.7-5**).

Figure 3.7-4 plots the percentage of avoidable price-out that can be eliminated at various levels of mitigation under each scheme, and **Figure 3.7-5** plots the percentage of avoidable monetary damage that can be eliminated at various levels of mitigation under each scheme. There are trade-offs of choosing one scheme over the other.

Strategy 1 (based on PAI losses) eliminates all avoidable price-out with an additional 6% of residences mitigated (on top of the 25% that is presently mitigated), while Strategy 2 (based on AD losses) only eliminates this with an additional 43% of residences mitigated (or at close to three times the amount presently mitigated). At an additional 21% of residences mitigated (or at close to twice the amount presently mitigated), Strategy 2 eliminates the majority (or 75%) of avoidable price-out.

Also, Strategy 2 eliminates the majority (or 75%) of avoidable monetary damage with an additional 13% of residences mitigated (on top of the 25% that is presently mitigated), while Strategy 1 eliminates this with an additional 19% of residences mitigated. So, compared to using Strategy 1, using Strategy 2 reaches peak performance in terms of expected number of households severely cost-burdened by monetary damage very quickly. However, Strategy 2 results in slightly reduced performance in terms of expected monetary damage.

A combination of these two prioritization schemes could fare well on both terms. With an additional 14% of residences mitigated, addressing 6% of the highest PAI losses, and then 8% of the highest AD losses after that, we could eliminate all avoidable price-out and the majority of avoidable monetary damage.

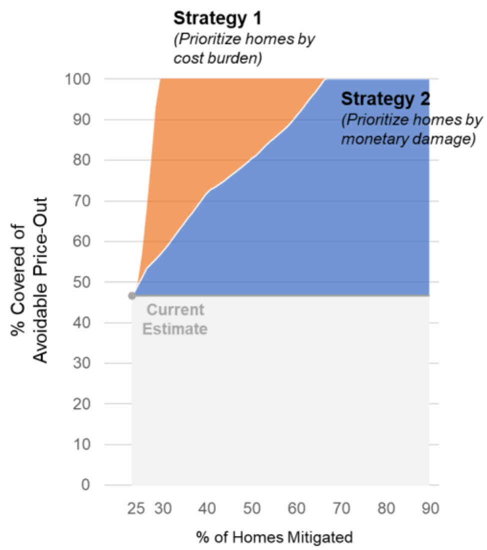

Figure 3.7-4. Percentage of avoidable price-out eliminated at various levels of mitigation under prioritization schemes; Strategy 1 refers to prioritizing residences based on cost burden, and Strategy 2 refers to prioritizing residences based on monetary damage.

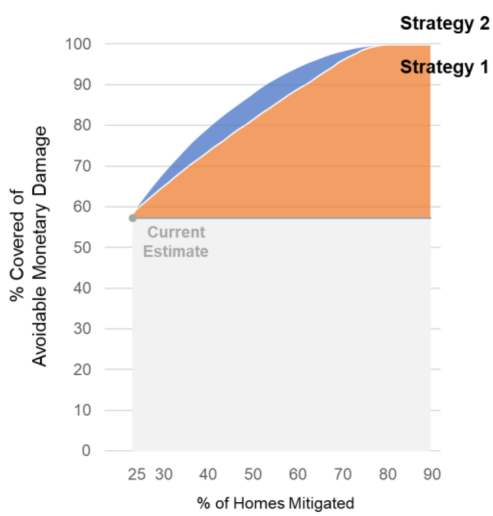

Figure 3.7-5. Percentage of avoidable monetary damage eliminated at various levels of mitigation under prioritization schemes; Strategy 1 refers to prioritizing residences based on cost burden, and Strategy 2 refers to prioritizing residences based on monetary damage.

3.8 Discussion

At the current level of mitigation, Miami-Dade, FL has a remaining $1.78 billion / year in expected monetary damage and 70,038 households / year facing risk of being priced out that could be prevented using the mitigation measures considered in this work. In the state of Florida, this amounts to $8.7 billion / year and 336,619 households / year, and across all six study states, this amounts to $117.2 billion / year and 443,512 households / year. Within each of the six states, the current level of mitigation eliminates less than half (even less one-third in some cases) of avoidable monetary damage and, separately, avoidable price-out.

The case study of Miami-Dade, FL shows how this analysis could be used for data-informed disaster risk reduction policy which addresses both monetary damage and its resulting cost burden with minimal effort. In fact, in that county, it is possible to address all avoidable price-out (i.e. eliminating risk to households who cannot afford repairs) as well as the majority of avoidable monetary damage simply by choosing the mitigated residences carefully and mitigating only 1% more residences than would be selected if addressing avoidable monetary damage were the only criteria.

There is increasing availability of support and resources for homeowners seeking to retrofit their residences. There are Federal and state programs for grants, loans, and insurance. Each of these programs require assessors make decisions every day about 'who' to protect. To aid this decision, we explore hurricane wind-related damages and repair needs from various metrics and mitigation prioritization schemes. Our simulated datasets and simulation code could be used by nonprofits and government agencies to identify the location of climatologically-, physically-, and/or socially-vulnerable households.

In its latest version, our methodology assumes that each household decision is independent. However, mitigating multi-unit housing would impact several households at once. Our code could be updated to incorporate dependencies among households in multi-unit housing. Our code could also incorporate dependencies among households in the same community (e.g., Census Block Group or Census Tract), to capture community-level impacts of mitigation. Also, the 'per-annual-income' (PAI) approach might be more relevant for homeowners, rather than renters. This approach could be refined for the experiences of renters.

Lastly, futures studies could consider the cost of applying mitigation measures. The cost model is derived from the RSMeans labor and materials cost database (FEMA 2021b). This database could be used to derive costs for items like shutters (Torkian et al., 2014). Such an analysis would enable the study of the extent of mitigation achievable under budget constraints, where addressing one property of higher value could be costlier than addressing multiple lower-value properties.

3.9 Data Availability Statement

All data, models, or code generated or used during the study are available for the corresponding author by request. This includes our simulated dataset and simulation code.

3.10 Acknowledgements

Research was carried out by the Concrete Sustainability Hub at MIT with funding provided by the Portland Cement Association (PCA) and the Ready Mixed Concrete (RMC) Research and Education Foundation.

3.11 Declaration of Interest Statement

The authors report there are no competing interests to declare.

3.12 References

References can be found at the end of this work.

4 Contributions to Environmental Assessment: Project Level

This chapter includes the manuscript "House of Cards: Trade-Offs of Construction Material Choice in Hurricane-Prone Communities" authored by Ipek Bensu Manav and Randolph Kirchain. The title and content of the manuscript may have changed during peer review and publication.

4.1 Abstract

With increasing demands for 'green' buildings, it is critical to develop rigorous methods to quantify how 'green' a building is. Such methods derive environmental impact measures, the most common of which is greenhouse gas (GHG) emissions.

Building life cycle emissions consist of embodied and operational emissions. Present studies of building emissions are typically limited to embodied emissions, and studies of building embodied emissions are typically limited to the product and construction stages. However, the majority of building life cycle emissions derive from the later use and end-of-life stages, which include emissions from repair, replacement, and operational energy usage.

In this manuscript, hazard vulnerability and carbon uptake are incorporated into building embodied emissions. Then, embodied emissions are combined with operational emissions to capture the full life cycle of emissions associated with construction material choice. The case study explores outcomes for concrete, masonry, and wood homes in Miami-Dade, FL. Expanding the case study to the entire state, outcomes are mapped for exterior wall core material choice.

Model results show that a durable, hazard-resilient material like concrete may lead to higher emissions in the initial construction stage, while also contributing to lower life cycle emissions, thanks to savings in the repair and replacement stages. The case study highlights concrete as the favorable material option in coastal and more southern communities, where hurricane wind exposure is relatively higher, and wood as the favorable material option in inland and more northern communities, where hurricane wind exposure is relatively lower.

4.2 Keywords

Hurricanes, Loss Estimation, Life Cycle Assessment

4.3 Introduction

Residential buildings are widely recognized as a major contributor of greenhouse gas (GHG) emissions (Lucon et al., 2014). Thus, buildings are becoming a central topic for discourse around climate mitigation and adaptation.

To aid the increasing demand for ‘green’ buildings, various institutions offer building rating systems, such as the U.S. Green Building Council’s (USGBC’s) Leadership in Energy and Environmental Design (LEED) program. This program is based on a set of prescriptive measures (USGBC, n.d.). Such programs focus on initial design and construction, rather than the entire building life cycle, though ignoring use and end-of-life leads to mal-informed decision-making. An example of such decision-making is jeopardizing the durability and hazard resilience of buildings by promoting lightweight construction in communities exposed to natural hazards.

To address concerns around hazard resilience, an increasing number of institutions offer building rating systems specialized in this regard, such as the Institute for Business and Home Safety’s (IBHS’s) FORTIFIED program for buildings in hurricane-prone communities. Similar to LEED, this program is based on prescriptive measures (IBHS, n.d.), albeit a completely separate set from those covered in LEED, failing to bridge the two perspectives. As a result, the pursuit of sustainable (i.e. ‘green’) buildings and resilient buildings, though inextricable, are deeply extricated in practice.

A similar trend follows for sustainability and resilience assessments. Life cycle assessment (LCA), a common tool for sustainability experts, in theory, captures environmental impacts arising from the entire building life cycle. However, present LCA studies ignore hazard repair and replacement demands in their estimate of embodied emissions. On the other hand, loss estimation, a common tool for resilience experts, deals with a variety of different metrics (e.g. dollar value of expected damages, number of households expected to displace), but falls short of translating those metrics to environmental measures (e.g. GHG emissions associated with repairing expected damages).

In this manuscript, we start bringing these two perspectives together to better represent the outcomes of construction material choice in single-family dwellings in hurricane-prone communities. By forging a more complete model for building LCA, we incorporate hazard vulnerability into the discussion of what makes a home ‘green’. In doing so, we demonstrate that the material choice that is more carbon-intensive to build with can lead to lower life cycle emissions, if that option is used in a climatological context where it provides significant benefits compared to its competitor in terms of durability and hazard resilience.

4.4 Literature Review

Building emissions comprise of product (A1-3), construction (A4-5), use (B), and end-of-life (C) emissions. Portions of these emissions can be characterized as either *embodied* or *operational*, associated with consumption of either materials or operational energy (i.e. electricity and fuels).

Analyzing building emissions relies on itemizing activities and assigning them schedules. Activities can be as large as pouring concrete for a slab foundation or as small as changing a lightbulb. Schedules can be as infrequent as only once (e.g. the foundation) or as frequent as every few years (e.g. the lightbulb). Defining activities and schedules depends on assumptions, which are often better defined for earlier (i.e. product and construction) stages, and less so for latter (i.e. use and end-of-life) stages.

In studies of building embodied emissions, use-stage emissions are the "most neglected" (Pomponi & Moncaster, 2016). Pomponi and Moncaster conducted a review of 77 such studies and found that 90% account for product (A1-3) stage, 50% account for construction (A4-5) stage, and 30% account for end-of-life (C) stage, while only 20% account for use (B) stage (2016). Even in studies which consider B-stage emissions, we identified two major gaps pertinent to evaluating decisions like construction material choice: neglect of hazard vulnerability and either neglect or overstatement of carbon uptake.

First, there are a few embodied emission studies which consider B3 (repair) emissions, and they fail to incorporate the impacts of hazard vulnerability. By assuming steady-state conditions, these studies limit activities to regular wear-and-tear and ignore extreme conditions such as those which lead to damage from natural hazard exposure. (A similar trend follows for studies which consider B2 (maintenance), B4 (refurbishment), and B5 (replacement) emissions.)

Studies which consider B2-5 emissions cover a variety of building components: mechanical, electrical, and plumbing (MEP) (e.g. inspecting boilers annually) (Blengini & Di Carlo, 2010; Brown et al., 2014; Lee et al., 2009; Moncaster & Symons, 2013; Onat et al., 2014), finishing (e.g. cleaning façade annually) (Blengini & Di Carlo, 2010; Moncaster & Symons, 2013; Pomponi et al., 2015), and insulation (e.g. upgrading insulation) (Brown et al., 2014; Moncaster & Symons, 2013; Onat et al., 2014). Schedules derive from literature (Baek et al., 2013; Blengini & Di Carlo, 2010), contractor surveys (Blengini & Di Carlo, 2010), national surveys (Brown et al., 2014; Lee et al., 2009; Onat et al., 2014), and databases (Moncaster & Symons, 2013). Activities and schedules are influenced by building age (Lee et al., 2009), type (Onat et al., 2014; Vukotic et al., 2015), materials (Alshamrani et al., 2014; Vukotic et al., 2015), and climate (e.g. hot or cold, wet or dry) (Basbagill et al., 2013). Climate factors do not include natural hazard exposure (Basbagill et al., 2013). Most authors assume structural components are "permanent" (Vukotic et al., 2015). Some acknowledge high-strength materials "expand the lifespan" of buildings (Baek et al., 2013). However, this effect is left out of modeling on the basis that there is "little reliable information" (Blengini & Di Carlo, 2010).

Although the environmental impacts of natural hazards have not yet been studied rigorously, their economic impacts have been the subject of various areas of study: loss estimation (Pita et al., 2015), cost-benefit analysis (Li, 2012; Torkian et al., 2014), and life cycle cost assessment (LCCA) (Dong & Frangopol, 2017; Mahmoud & Cheng, 2017; Noshadravan et al., 2017). These areas of study allow us to assess activities and schedules associated with damage and repairs. For instance, hurricanes lead to varying degrees of damage, ranging from loss of nonstructural components (e.g. roof shingles), to loss of structural components (e.g. roof decking), to loss of the entire building. The extent and frequency of damage relies on structural (e.g. decking material) and climatological (e.g. frequency of storms) vulnerability. The combination of all these considerations allows to assess demands for repair and replacement.

Hurricane loss estimation models span a range of scales from building components (e.g. roof panels) (Li & Ellingwood, 2006) to building archetypes (e.g., wood-frame single-family dwellings) (Li & van de Lindt, 2012). These models are employed to study Census Tracts (Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006), counties (Hamid et al., 2011), and actuarial portfolios (AIR, 2019; ARA, 2019; CoreLogic, 2019; RMS, 2019). These studies are then applied to the cost-benefit analysis of various mitigation measures (Li, 2012; Torkian et al., 2014) and the LCCA of buildings (Dong & Frangopol, 2017; Mahmoud & Cheng, 2017; Noshadravan et al., 2017). In **Chapters 2 & 3** of this work, we discuss how integrating texture (i.e. density and configuration of surrounding buildings) into loss estimation enables us to calculate expected damages for each individual buildings in an area of study in a computationally inexpensive manner (Manav et al., 2022). We make this integration using the Hazards U.S. Multi-Hazard (HAZUS-MH) model developed by the U.S. Federal Emergency Management Agency (FEMA) (Vickery, Lin, et al., 2006; Vickery, Skerlj, et al., 2006), as all other regional loss estimation models are currently proprietary.

Second, there are fewer embodied emission studies which consider B1 (operational use) emissions. These emissions occur without active intervention from building occupants or managers, an example being carbon uptake. Through carbon uptake (or carbonation), concrete surfaces absorb atmospheric carbon dioxide in a chemical process which reverts its drying. Carbon uptake has been studied extensively by material scientists and structural engineers, as carbonation leads to a progressively acidic concrete medium and poses a threat to the steel reinforcement bars embedded inside of it. Increasingly, carbon uptake is recognized as an opportunity, rather than a threat, because it provides a passive mechanism through which atmospheric carbon dioxide is sequestered (IPCC, 2022). Studies which consider carbon uptake assume lofty lengths for building lifespan and second life (García-Segura et al., 2014). Overstating the potential for carbon sequestration through carbon uptake, however, hinders efforts to neutralize and reduce GHG emissions, by underestimating the portion of emissions which require active intervention (e.g. design optimization). In recent conference proceedings, we propose a set of realistic assumptions for the use and end-of-life carbon uptake of cement-based products (CBPs) (e.g. ready-mixed concrete) in buildings (AzariJafari et al., 2023).

Lastly, building LCA addresses both embodied and operational emissions, creating a more comprehensive assessment of building emissions. In this manuscript, we extend the Building Attribute-to-Impact Algorithm (BAIA), developed by colleagues at the MIT Concrete Sustainability Hub (CSHub), to incorporate hazard vulnerability and carbon uptake into the LCA of single-family dwellings. BAIA is pliable to study regional impacts of natural hazards thanks to its use of underspecification. Streamlined LCA (or underspecified LCA) allows to generate LCA results under conditions where some model inputs are missing (albeit with a band of uncertainty to follow) (Hester et al., 2018). This functionality accommodates gaps in user knowledge, as conventional LCA can be prohibiting due to the data-intensive, data-dependent nature of the practice. For our purposes, we make use of streamlined LCA to study the regional housing stock based on publicly-available housing surveys, which definitely do not cover all details necessary for conventional LCA.

4.5 Methodology

The objective of this study is to conduct a regional assessment of the outcomes of construction material choice in single-family dwellings in hurricane-prone communities. To do this, we apply a streamlined LCA model updated to include impacts of hazard vulnerability and carbon uptake. Ideally, we would have applied this model on a dataset of every new home permitted to be built in a year of interest, where all building characteristics are known. However, in the U.S., not all characteristics are tracked, while others are found across several datasets aggregated on various levels at much less granular scales (e.g. Census Division).

To address this, we simulate 5,000 actualizations of a typical home under 100 wind loading scenarios in each Census Tract, making use of locational data to infer climatological and building characteristics. For each actualization b, we then match up this information with damage, cost, and emission models to evaluate the full life cycle of emissions associated with its initial construction, repair, replacement, and operational energy usage. Our methodology consists of four aspects: [1] creating building archetypes, [2] incorporating expected damages into LCA results, [3] parameterizing carbon uptake, and [4] conducting statistical testing to evaluate outcomes.

For this, we use the BAIA LCA model, the HAZUS loss estimation model, and the plentitude of building characteristic assumptions underlying each of these models. Wherever possible, these assumptions are supplemented by data from the U.S. Census Bureau's American Housing Survey (AHS). Combined in a single framework, these models and data allow us to evaluate the context dependency of building life cycle emissions.

Creating Building Archetypes

In this study, we create comparative samples to explore building life cycle emissions and the influence of exterior wall core material choice on such in single-family dwellings. Specifically, the exterior wall core material can be concrete (i.e. insulated concrete form (ICF) wall core), masonry (i.e. concrete masonry unit (CMU) or concrete block wall core), or wood (i.e. light-frame, wood stud wall core).

To span the entire sample space, we simulate 5,000 actualizations of a typical home represented by present tools and data. This sample space is characterized by a variety of inputs pertinent to: [1] both BAIA and HAZUS, [2] only one of BAIA or HAZUS, or [3] the carbon uptake model.

Under category [1], each actualization b is assigned: number of stories (1, 2, or 3), living area (small, medium, or large), roof shape (gable or hip), roof cover (asphalt shingles, concrete tiles, or metal cladding), and window area (low, medium, or high). Information for the first two (i.e. number of stories and living area) derive from 2018 AHS data (respectively, 'STORIES' and 'UNITSIZE' in the metadata) (U.S. Census Bureau, 2019), while the latter three derive from the HAZUS database (FEMA, 2021b).

In HAZUS, discrete variables (e.g. number of stories, roof shape, and roof cover) are sampled based on their prevalence in the model's 2018 update (FEMA, 2021b). In BAIA, such variables are sampled simply as equally likely options (Hester, 2018). Thus, wherever possible, we make use of the building characteristic prevalences found in the HAZUS database (or AHS data).

Since BAIA depends on computing the exact building geometry, continuous variables (e.g. living area and window area) are sampled from a range represented by a uniform distribution

(Hester, 2018). (In HAZUS, living area is a deterministic function of other building characteristics, while window area is treated as a discrete variable.)

Living area for 'small' homes is sampled from 100-183 m^2 ('UNITSIZE' = 1, 2, 3, 4, or 5), 'medium' from 183-267 m^2 ('UNITSIZE' = 6 or 7), and 'large' from 267-350 m^2 ('UNITSIZE' > 7). Their probabilities derive from AHS data and are grouped based on number of stories (e.g. homes with more stories likelier to have larger living area) (U.S. Census Bureau, 2019).

Moreover, window-to-wall ratio (WWR) for homes with 'low' window area is sampled from .17-.25, 'medium' from .25-.33, and 'high' from .33-.4. Their probabilities derive from the HAZUS database. BAIA inputs front, back, and side WWRs separately (Hester, 2018). For simplicity, we assume the same WWR for front and back facades, and sample side WWR from .1-.17.

The complete list of building characteristics input to HAZUS can be found in **Table 4.5-1** (including several characteristics which fall under [2]). In HAZUS, these characteristics are referred to as wind building characteristics (WBCs) (FEMA, 2021b). A complete set of information for b in the HAZUS model allows us to assign damage functions and compute expected damages in terms of a percentage of total replacement cost of each b. Damage functions are modeled based on 2018 RSMeans data on labor and material costs (FEMA, 2021b).

The complete list of building characteristics input to the BAIA operational energy model can be found in **Table 4.5-2** (including several characteristics which fall under [2]). In BAIA, these characteristics are referred to as Attribute-to-Activity Model for Energy (AAME) inputs (Hester, 2018). Additionally, the BAIA materials model inputs information about the exact building geometry, subassembly configurations, and material definitions (Hester, 2018). A complete set of information for b in the BAIA operational energy and materials models allows us to model replacement schedules, energy costs and emissions, and labor and material cost and emissions. This, in turn, allows us to compute emissions associated with the initial construction, replacement, and operational energy usage of each b. Replacement schedules derive from industry standards, material emissions from life cycle inventories (LCIs), energy cost and emissions from 2018 electrical grid data, and other costs from 2018 RSMeans data (similar to HAZUS) (Hester, 2018).

Moreover, under category [3], each b is assigned: presence of basement (yes or no) and foundation type (slab foundation, basement, partial basement, or crawlspace). Information for these derive from 2018 AHS data (respectively, ‘GARAGE’ and ‘FOUNDTYPE’ in the metadata) (U.S. Census Bureau, 2019). Both are treated as discrete variables.

Lastly, each b is assigned a service life (or lifespans) from a survival rate fitted to Weibull distribution. Formally, that is

$$P_b(ls) = Weibull(l, 2.8, 73.5) \quad \text{Eq.3.5.1}$$

where $P_b(ls)$ is the probability that b has a service life less than or equal to ls, given Weibull shape parameter 2.8 and scale parameter 73.5 (Aktas & Bilec, 2012).

Based on this survival rate, the average service life is 66 years. Practically, more durable and hazard resilient construction materials contribute to longer service lives (Baek et al., 2013). However, in LCA, this contributes to higher life cycle emissions, as use-stage emissions scale proportionally to service life. To circumvent this dichotomy, we assume the same survival rate for homes with concrete, masonry, and wood exterior wall core options. Rather than shortened service lives, we represent compromised performance through increased repair and replacement demands. Cases where such demands exceed initial construction emissions can be interpreted as cases where the given b would need to be torn down and rebuilt to ensure the given service life.

Incorporating Expected Damages into LCA Results

As described earlier, the HAZUS model allows us to compute expected damages as a percentage of total replacement cost of each actualization b. The HAZUS database includes damage functions as well as terrain and wind speed recurrence data (FEMA, 2021b). The former is available for each wind building type (WBT) (defined by WBCs listed in **Table 4.5-1**). The latter is available for each Census Tract.

Hazard repair demands are driven by residing in a Census Tract with high hurricane exposure and/or in a building susceptible to incurring damages when exposed to hurricane wind loading. Wind speed recurrence data is fitted to Weibull distributions and captures the annual probability of each wind speed, represented as

$$P_{t,\tau}(ws) = Weibull(X_t, Y_t) \qquad \text{Eq.3.5.2}$$

where $P_t(ws)$ is the probability that Census Tract t experiences wind speeds less than or equal to ws on year τ, given Weibull shape parameter X_t and scale parameter Y_t.

Damage data is fitted to normal distributions to create damage functions which capture the expected damages at each wind speed and terrain definition (e.g. urban, suburban, or rural), represented as

$$\phi_b(ws) = Normal(ws, \mu_{b,t}, \sigma_{b,t}) \qquad \text{Eq.3.5.3}$$

where $\phi_b(ws)$ is the expected damages that b incurs under wind speed ws, given normal parameters $\mu_{b,t}$ and $\sigma_{b,t}$ derived from the WBT of b and terrain definition of Census Tract t.

We simulate 100 hurricane wind loading scenarios in each Census Tract. To define the analysis period, we identify the longest service life among 5,000 actualizations. Then, we sample wind speeds for each year within that analysis period. Under a given scenario, the sampled wind speeds (and terrain) are the same for all each b within a Census Tract. This leads to the relationship

$$P_{b,\tau}(ws) = P_{t,\tau}(ws) \qquad \text{Eq.3.5.4}$$

where $P_{b,\tau}(ws)$ is the probability that b in Census Tract t experiences wind speeds less than or equal to ws on year τ.

Whether or not, or to what extent, each b incurs damages depends on its damage function. We combine **Eq.3.5.3** and **Eq.3.5.4** as

$$\phi_{b,\tau}(ws) = Normal(ws, \mu_{t,\tau}, \sigma_{t,\tau}) \qquad \text{Eq.3.5.5}$$

where $\phi_{b,\tau}(ws)$ is the expected damages that b incurs under wind speed ws on year τ.

Moreover, each b only incurs expected damages on year τ as long as it has not yet reached the end of its service life ls. Thus, the expected damages each b incurs over its service life is a sum of expected damages it incurs on each year $\tau \le ls$. That is

$$\%Rr_b = \sum_{\tau \le ls} \phi_{b,\tau}(ws) P_{b,\tau}(ws) \qquad \text{Eq.3.5.6}$$

where $\%Rr_b$ is the expected damages that b incurs over its service life. This is represented as a percentage of b's replacement cost.

In HAZUS, replacement cost is a deterministic function of living area, presence of garage, presence of basement, and Census Block Group (each corresponds to a cost correction factor). This function is generalized from initial construction costs. Instead of HAZUS replacement costs, we opt to use BAIA initial construction costs (and emissions), as these are unique to each actualization.

To combine expected damages with replacement emissions, we make use of subassembly loss ratios. HAZUS technical manual provides these ratios to break down entire building damages to building components. For simplicity, we assume subassembly damages are equally distributed across relevant building components. Then, we multiply subassembly expected damages by the relevant replacement emissions. That is

$$Rr_{bc} = TR_{bc} LR_{bc} \%Rr_{b} \qquad \text{Eq.3.5.7}$$

where Rr_{bc} is the emissions associated with the expected damages that building component bc found in b incurs over its service life, TC_{bc} is its total replacement emissions, LR_{bc} is its HAZUS subassembly loss ratio, and $\%Rr_{b}$ is the expected damages that b incurs as a percentage of b 's replacement cost.

Thus, the emissions associated with the expected damages that each b incurs over its service life is a sum of expected damages it incurs on each building component. That is

$$Rr_{b} = \sum_{bc \in b} Rr_{bc} \qquad \text{Eq.3.5.8}$$

where Rr_{b} is the emissions associated with the expected damages that b incurs over its service life and Rr_{bc} is the emissions associated with the expected damages that building bc found in b incurs.

Working on the scale of subassemblies and building components is critical because some of the most carbon-intensive subassemblies (e.g. foundation) incur no damages under hurricane wind loading, so applying expected damages on the entire building scale could lead to overestimating emissions associated with hazard repair demands.

Parameterizing Carbon Uptake

To account for carbon uptake, we apply the same framework as the C-Up model (AzariJafari et al., 2023). In this framework, the carbon uptake of each building b is a sum of carbon uptake on each surface on each building component. That is

$$CU_b = \sum_{f \in bc} \sum_{bc \in b} CU_{f,bc} \qquad \text{Eq.3.5.9}$$

where CU_b is the carbon uptake of b and $CU_{f,bc}$ is the carbon uptake on face f of building component bc found in b.

After computing surface areas and volumes, we apply carbon functions to estimate the potential for carbon uptake. These functions rely on the type of CBP, compressive strength, mix design, and exposure conditions. This can be shown as

$$U_{f,bc} \propto CBP_{bc}, CS_{bc}, MD_{bc}, EC_{f,bc} \qquad \text{Eq.3.5.10}$$

where $U_{f,bc}$ is the unit carbon uptake on face f of building component bc found in b, CBP_{bc} is its material definition (i.e. concrete or mortar), CS_{bc} is its compressive strength (e.g. 15-25 MPa), MD_{bc} is its mix design (e.g. substitution of portland cement by slag and/or flyash), and $EC_{f,bc}$ is its exposure condition (e.g. indoor, unfinished).

CBPs contribute to carbon uptake throughout the product (A1-3) and construction (A4-5) stages (i.e. carbonation of cement wastage), use (B) stage, and end-of-life (C) stage of buildings. That is

$$CU_{f,bc} = CU_{f,bc}^{waste} + CU_{f,bc}^{use} + CU_{f,bc}^{EoL} \qquad \text{Eq.3.5.11}$$

where $CU_{f,bc}$ is the carbon uptake on face f of building component bc found in b, given a service life of τ and end-of-life period of τ', $CU_{f,bc}^{waste}$ is the carbon uptake associated with cement wastage, $CU_{f,bc}^{use}$ is the B-stage carbon uptake, and $CU_{f,bc}^{EoL}$ is the C-stage carbon uptake.

Specifically, we assume 97% of cement consumed is bulk and 3% bagged, and that 2% and 15% of bulk and bagged cement, respectively, gets wasted (AzariJafari et al., 2023). The potential for carbon uptake associated with cement wastage is a function of t and wasted volume (AzariJafari et al., 2023), shown as

$$CU_{f,bc}^{waste} \propto \%CW_{f,bc} V_{f,bc} U_{f,bc}^{waste} \qquad \text{Eq.3.5.12}$$

where $CU_{f,bc}^{waste}$ is the carbon uptake associated with cement wastage on face f of building component bc found in b, given a total carbonation period of t, $\%CW_{f,bc}$ is its percentage of cement wastage, $V_{f,bc}$ is its volume, and $U_{j,bc}^{waste}$ is the unit carbon uptake associated with cement wastage based on **Eq.3.5.10**.

B-stage carbon uptake is a function of $\sqrt{\tau}$ and surface area (AzariJafari et al., 2023), shown as

$$CU_{f,bc}^{use} \propto SA_{f,bc} U_{f,bc,\tau}^{use} \sqrt{\tau} \qquad \text{Eq.3.5.13}$$

where $CU_{f,bc}^{use}$ is the B-stage carbon uptake on face f of building component bc found in b over its service life τ, $SA_{f,bc}$ is its surface area, and $U_{f,bc}^{use}$ is the unit B-stage carbon uptake based on **Eq.3.5.10**.

C-stage carbon uptake is a function of $\sqrt{\tau'}$ and uncarbonated volume (AzariJafari et al., 2023), shown as

$$CU_{f,bc}^{EoL} \propto UV_{f,bc} U_{f,bc}^{EoL} \sqrt{\tau'} \qquad \text{Eq.3.5.14}$$

where $CU_{f,bc}^{EoL}$ is the C-stage carbon uptake on face f of building component bc found in b, $UV_{f,bc}$ is its uncarbonated volume, and $U_{f,bc}^{EoL}$ is the unit C-stage carbon uptake based on **Eq.3.5.10**.

We assume concrete applications have τ' of 6 months, during which they contribute to C-stage carbon uptake, while mortar applications are fully-carbonated during their service life (within approximately 15 years), so they do not contribute to C-stage carbon uptake. Since our cut-off is at end-of-life, we ignore second-life carbon uptake.

We carry out this calculation for all relevant surfaces and volumes. These surfaces and volumes include foundation systems, basement walls, and exterior walls (excluding windows and exterior doors). Regardless of the exterior wall core material, all homes (except those with crawlspaces) are assumed to have concrete slab foundations and footings. All homes with basements (partial or full) are assumed to have CMU basement walls. Concrete and masonry homes are assumed to have concrete or CMU exterior walls, respectively. Volumes exclude steel reinforcement in concrete components (1-2% of cross-section) and hollow sections in CMU components (only counting for the shells and webs). CMUs are assumed the standard 20 cm (8'') by 40 cm (16'').

As stated earlier, carbon uptake relies on compressive strength and mix design. Concrete components are applied the 15-25 MPa concrete carbon uptake model, while CMU components are applied the mortar carbon uptake model. Mix design information derives from National Ready-Mixed Concrete Association (NRMCA) data for U.S. regions.

Lastly, exposure conditions influence the rate and degree of carbonation. Possible exposure conditions are inground (e.g. slab foundation), indoor, unfinished (inner side of basement walls), indoor, finished (inner side of exterior walls), outdoor, sheltered from rain (outer side of exterior walls on dry days), or outdoor, exposed to rain (outer side of exterior walls on rainy days). Carbon uptake on outdoor surfaces are a weighted average based on the local breakdown of dry and rainy days.

Conducting Statistical Testing to Evaluate Outcomes

To recap, we are interested in comparing outcomes of exterior wall core material choice. To do this, we simulate 5,000 actualizations of typical homes under 100 wind loading scenarios in hurricane-prone communities. Each actualization b enables a comparative sample of life cycle emissions for concrete, masonry, and wood exterior wall core options. These life cycle emissions include initial construction, repair, replacement, and operational energy usage emissions. Formally, that is

$$LC_b = IC_b + Rr_b + Rt_b + EU_b \qquad \text{Eq.3.5.15}$$

where LC_b is the life cycle emissions of b, IC_b is its initial construction emissions, Rr_b is its hazard repair emissions, Rt_b is its replacement emissions, and EU_b is its operational energy usage emissions.

Unless denoted by a letter and/or number code, we use the terms ‘initial construction’, ‘repair’, and ‘replacement’ to refer to the sum of life cycle activities associated with a stream of material consumption. Hence, initial construction, repair, and replacement emissions, each, include relevant product, construction, and end-of-life emissions. Additionally, CBPs consumed contribute to carbon uptake. Together, that is

$$X_b = P_{x,b} + C_{x,b} + EoL_{x,b} + CU_{x,b} \qquad \text{Eq.3.5.16}$$

where X_b is the emissions of X (initial construction, repair, or replacement) of b, $P_{x,b}$ is its product emissions, $C_{x,b}$ is its construction emissions, $EoL_{x,b}$ is its end-of-life emissions, and $CU_{x,b}$ is its carbon uptake associated with CBPs consumed.

To study the benefits of each exterior wall core option, we conduct statistical testing of building stage emissions. We observe the differences wood-minus-concrete, masonry-minus-concrete, and wood-minus-masonry, as well as each flipped. Then, we run a signed rank test (a non-parametric test) to compute statistical significance to the differences. (We do not satisfy the conditions for a t-test (a normal test) as most differences are not normally distributed and have significant outliers.)

To identify which exterior wall core option is overall advantageous, we conduct similar statistical testing. For hazard repair demands, we highlight two of the 100 scenarios: median and 95th-percentile. The median is intended to be representative (since life cycle repair demands are themselves a sum of random samples, they fall under the law of large numbers and show a normal distribution, hence the median is the mean). The 95th-percentile is intended for design (as engineering principles favor).

Lastly, to combine multiple comparisons, we apply the Bonferoni principle and add the statistical significance of the differences. Then, we can map the ranking of the exterior wall core options based on life cycle emissions.

Table 4.5-1. List of HAZUS wind building characteristics (WBCs).

Code	Description
rship	Roof shape hip
rsgab	Roof shape gable
rcshg	Roof cover asphalt shingles
rccnt	Roof cover concrete tiles
rcmet	Roof cover metal cladding
walow	Window area low
wamed	Window area medium
wahig	Window area high
swrys	Secondary water resistance present
swrno	No secondary water resistance
rda6d	Roof decking 6d @ 6''/12''
rda8d	Roof decking 8d @ 6''/12''
rda6s	Roof decking 6d @ 6''/6''
rda8s	Roof decking 8d @ 6''/6''
tnail	Roof-to-wall connections toenails
strap	Roof-to-wall connections straps
shtys	Shutters present
shtno	No shutters
gdnod	No garage door (homes w/o shutters)
gdkwd	Garage door weak (homes w/o shutters)
gdstd	Garage door standard (homes w/o shutters)
gdno2	No garage door (homes w/ shutters)
gdsup	Garage door superior (homes w/ shutters)
rmfys	Masonry reinforcement present
rmfno	No masonry reinforcement

Table 4.5-2. List of BAIA Attribute-to-Activity Model for Energy (AAME) inputs.

Code	Description
LivingArea	Living area (sqft)
Bedrooms	Bedrooms
Stories	Stories
AspectRatio	Aspect ratio
DegreesFromS	Degrees from south (deg)
RoofType	0 = gable, 1 = hip
RoofPitch	Roof pitch
FrontWWR	Front window-to-wall ratio
BackWWR	Back window-to-wall ratio
SideWWR	Side window-to-wall ratio
WallU	U-value of exterior walls (W/m2K)
SlabU	U-value of slab foundation (W/m2K)
RoofU	U-value of roof (W/m2K)
WinU	U-value of windows (W/m2K)
WinSHGC	Solar heat gain coefficient of windows
HeatingShadeFactor	Heating shade factor
CoolingShadeFactor	Cooling shade factor
OverhangLength	Overhang length (ft)
ACH50	Air leakage rating
VentHeatRecoveryRate	Ventilation heat recovery rate
PctOpenWin	Percentage of openable windows
PctLED	Percentage of LED lightbulbs
WaterHeaterEff	Water heater efficiency
HeatingEff	Heating efficiency
CoolingEff	Cooling efficiency
HeatingSetPoint	Heating set point (F)
CoolingSetPoint	Cooling set point (F)

Note: several of these inputs depend on the building geometry and material definitions, such as window-to-wall ratios (depend on window and exterior wall areas) and U-values (depend on wall, roof, slab foundation, and window materials).

4.6 Case Study

To explore the relationship between natural hazard exposure and building life cycle emissions, we applied the methodology described in **Section 4.5** to analyze the outcomes of construction material choice in single-family dwellings across the hurricane-prone state of Florida. We present a detailed look at the results for the county of Miami-Dade, FL, and then summarize the results for the entire state.

The analysis of Miami-Dade County, FL is based on information from the 2018 updates for the BAIA and HAZUS models, as well as 2018 AHS data. As described earlier, this information is aggregated on various levels.

Locational information is necessary for both BAIA and HAZUS. HAZUS terrain and wind speed recurrence are available on Census Tract level (FEMA, 2021b). BAIA climate variables are available on county level (input to compute heating and cooling demands), and BAIA energy emissions are available on state level (Hester, 2018).

Building characteristic information is also necessary for both models. HAZUS characteristics are defined on schematic regional level, which can be larger or smaller than a state. In the case of Florida, the state is divided into four schematic regions: North Florida, Central Florida, South Florida, and Southeast Florida. Miami-Dade falls under Southeast Florida (FEMA, 2021b). AHS characteristics are defined on Census Division level (Southeast for Miami-Dade and Florida) (U.S. Census Bureau, 2019). BAIA characteristics are sampled depending on whether they are discrete or continuous. Discrete BAIA characteristics are sampled as equally likely options. Continuous BAIA characteristics are sampled from a uniform distribution. These distributions do not vary by location (Hester, 2018).

4.7 Results

The objective of this case study is to compare outcomes of exterior wall core material choice in single-family dwellings in Miami-Dade, FL and across the state of Florida. Our results consist of two parts: [1] comparing building life cycle emissions for example Census Tracts in the county, and [2] mapping exterior wall core material choice recommendations for all Census Tracts in the county and across the entire state.

Comparing Building Life Cycle Costs and Emissions

In this section, we compare building life cycle emissions for three example Census Tracts in Miami-Dade. **Figure 4.7-1** shows life cycle results for a Census Tract at a 'mid-level' of hurricane wind exposure (i.e. not too coastal or too inland, as exposure is highest on the coast, decreasing moving inland) (Census Tract 12086008416). **Figure 4.7-2** shows hazard repair results for two additional Census Tracts, one on the coast (labeled as 'higher' exposure) (Census Tract 12086004404) and one furthest inland (labeled as 'lower' exposure) (Census Tract 12086011500).

We found the largest differences in the product (A1-3) and construction (A4-5) stages (red areas in **Figure 4.7-1**) and the hazard repair (B3) stage (light blue areas in **Figure 4.7-1**). Our model results suggest that wood homes yield the lowest A-stage emissions. Considering most studies of building embodied emissions are limited to these stages (Pomponi & Moncaster, 2016), such studies would promote wood as the most eco-friendly (i.e. lower emissions) exterior wall core material. However, accounting for latter stage emissions and capturing a more complete picture of building life cycle emissions highlights concrete as the most eco-friendly exterior wall core material, especially in a climatological context that favors durable and hazard resilient construction materials.

Particularly, differences in the hazard repair (B3) stage are more pronounced in areas with higher hurricane wind exposure (top row of areas in **Figure 4.7-2**) and less pronounced in areas with lower hurricane wind exposure (bottom row of areas in **Figure 4.7-2**). This suggests a strong context dependency in evaluating the influence of hazard vulnerability the entire building life cycle.

While differences exist in the operational energy usage (B6) stage (hatched blue areas in **Figure 4.7-1**), the replacement (B4) stage (dark blue areas in **Figure 4.7-1**), and the end-of-life (C) stage (gray areas in **Figure 4.7-1**), these differences are much smaller than those in the product (A1-3), construction (A4-5), and hazard repair (B3) stages.

In these figures, carbon uptake (a negative emission) is removed from A-stage emissions. The total carbon uptake is roughly 1.7, 1.6, and 1.3 Mt carbon-dioxide-equivalent (CO2e) for concrete, masonry, and wood homes, respectively. Thus, carbon uptake sequesters a portion, albeit small, of building life cycle emissions.

We conducted Spearman rank correlation between building stage emissions and building characteristics. **Figure 4.7-3** shows Spearman rank correlation coefficients between building stage emissions for concrete archetypes and continuous inputs, **Figure 4.7-4** shows the same for categorical inputs. **Figure 4.7-5** shows Spearman rank correlation coefficients between the difference in building stage emissions for wood versus concrete archetypes and continuous inputs, **Figure 4.7-6** shows the same for categorical inputs. These figures are limited to inputs with at least one coefficient larger than .1 (or less than -.1). A complete list of inputs, as well as comparisons for masonry versus concrete and concrete versus masonry archetypes, can be found in the **Supplementary Materials**.

Lifespan, living area, and number of stories influence B4 and B6 emissions, but do not notably influence the differences in the same. Living area and number of stories do, however, influence both the net value of and differences in A1-5 and B3 emissions.

Percentage of openable windows, front and back WWRs, and heating and cooling efficiencies influence B6 emissions, but do not notable influence the differences in the same. Heating and cooling set points influence both the net value of and differences in B6 emissions. Additionally, differences in U-value of the exterior wall core influence the differences in B6 emissions.

Details about shutters, garage doors, and surrounding exposure conditions influence the net value of and differences in B3 emissions. Roof shape and roof deck attachment also influence the differences in B3 emissions. Moreover, roof shape influences A1-5 emissions (as it affects the amount of material consumed for the exterior wall system).

Figure 4.7-1 and **Figure 4.7-2** show *average* building stage emissions. Spearman rank correlation above also pertains to averages. In the remainder of this discussion, we refer to [1] initial construction, [2] repair and replacement, [3] operational energy usage, and [4] carbon uptake. [1] includes product (A1-3), construction (A4-5), and the relevant portion of end-of-life (C) activities. [2] includes repair (B3), replacement (B4), and the relevant portion of end-of-life (C) activities. [3] include operational energy usage (B6) activities. [4] includes cement wastage, use, and end-of-life carbon uptake.

In a Census Tract at a ‘mid-level’ of hurricane wind exposure, concrete homes, compared to wood, yield lower repair and replacement emissions in 97% of actualizations, lower operational energy usage emissions in 58% of actualizations, and greater carbon uptake in 100% of actualizations. Wood homes, compared to concrete, yield lower initial construction (including relevant product, construction, and end-of-life emissions) in 96% of actualizations. (Please refer to the **Supplementary Materials** for supporting boxplots.)

Concrete homes, compared to wood, yield lower life cycle emissions in 74% of actualizations. Compared to masonry, concrete homes yield lower life cycle emissions in 88% of actualizations, and wood homes yield lower life cycle emissions in 78% of actualizations. (Please refer to the **Supplementary Materials** for supporting boxplots.)

Moving forward in this discussion, it is important to note that all comparisons up to this point are based on the median scenario of wind loading for each actualization. In this climatological context (i.e. Census Tract and intensity), concrete is the most eco-friendly exterior wall core material, then wood, then masonry.

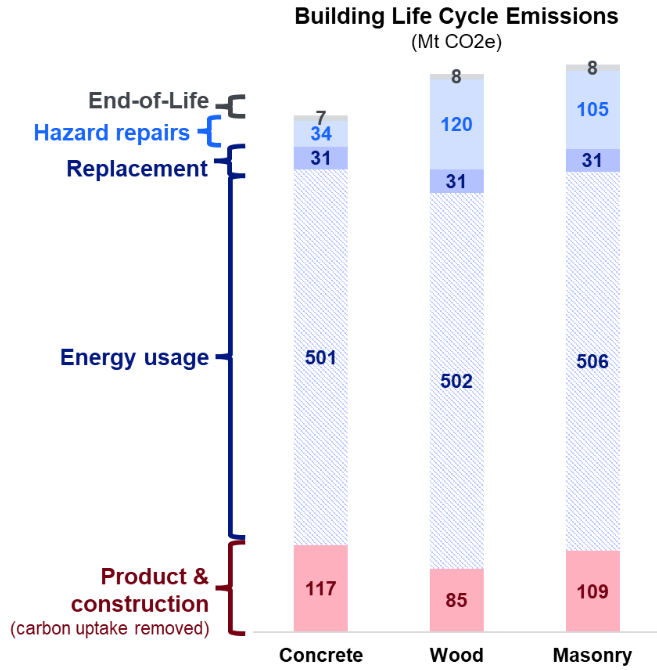

Figure 4.7-1. Building life cycle emissions for an example Census Tract in Miami-Dade, FL; mean of 1,000 actualizations, median scenario of 100 wind loading scenarios.

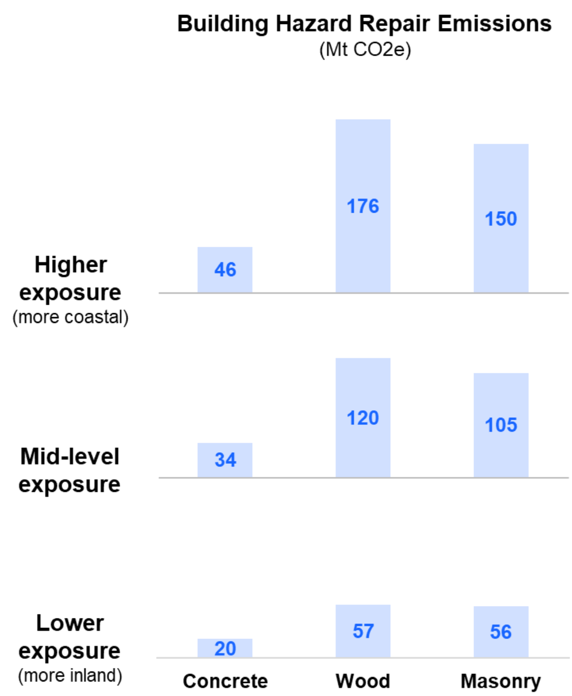

Figure 4.7-2. Building hazard repair emissions for example Census Tracts in Miami-Dade, FL; mean of 5,000 actualizations, median scenario of 100 wind loading scenarios.

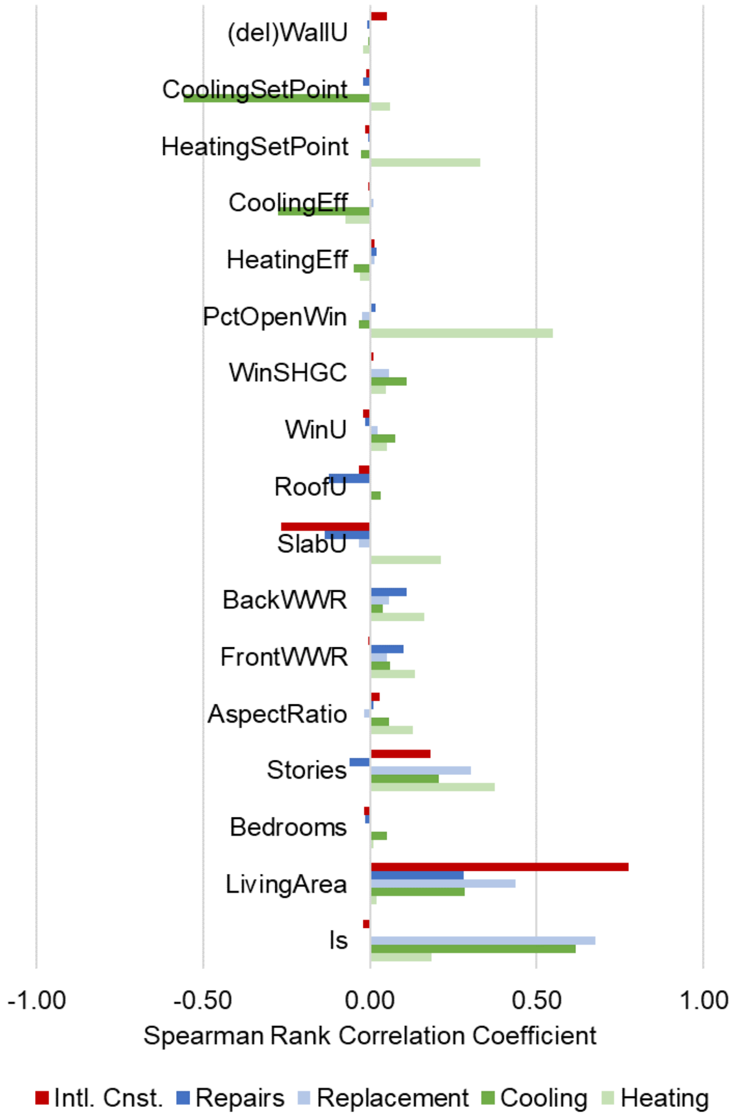

Figure 4.7-3. Spearman rank correlation between building stage emissions for concrete archetypes and continuous inputs; initial construction, repair, and replacement emissions exclude end-of-life emissions for the respective activity; figure shows inputs with at least one coefficient larger than .1 or less than -.1.

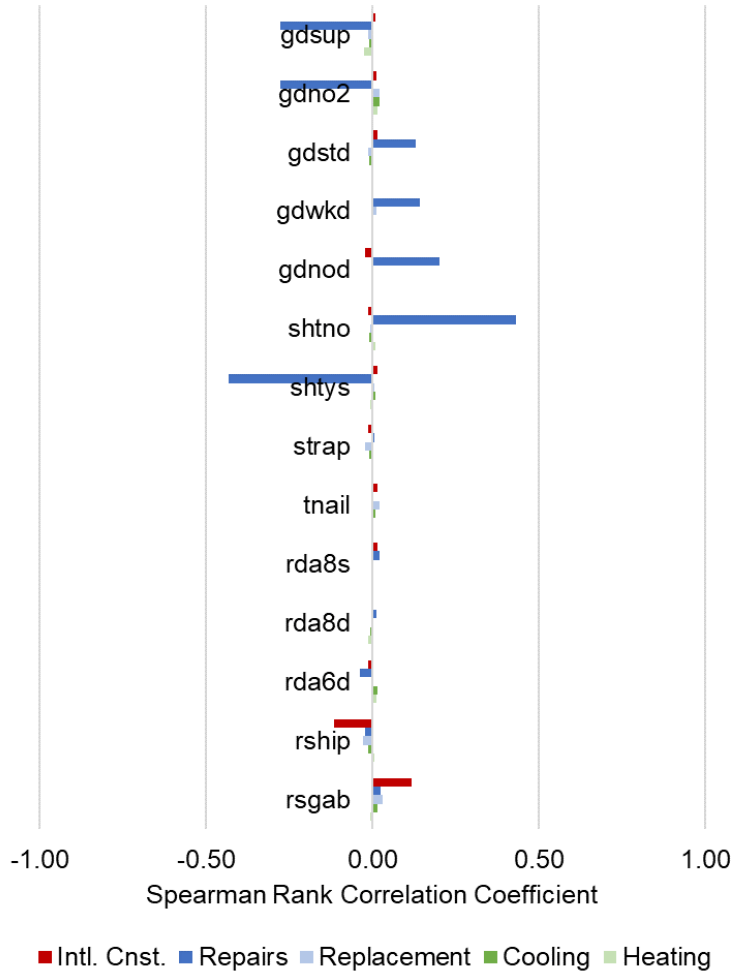

Figure 4.7-4. Spearman rank correlation between building stage emissions for concrete archetypes and categorical inputs; initial construction, repair, and replacement emissions exclude end-of-life emissions for the respective activity; figure shows inputs with at least one coefficient larger than .1 or less than -.1.

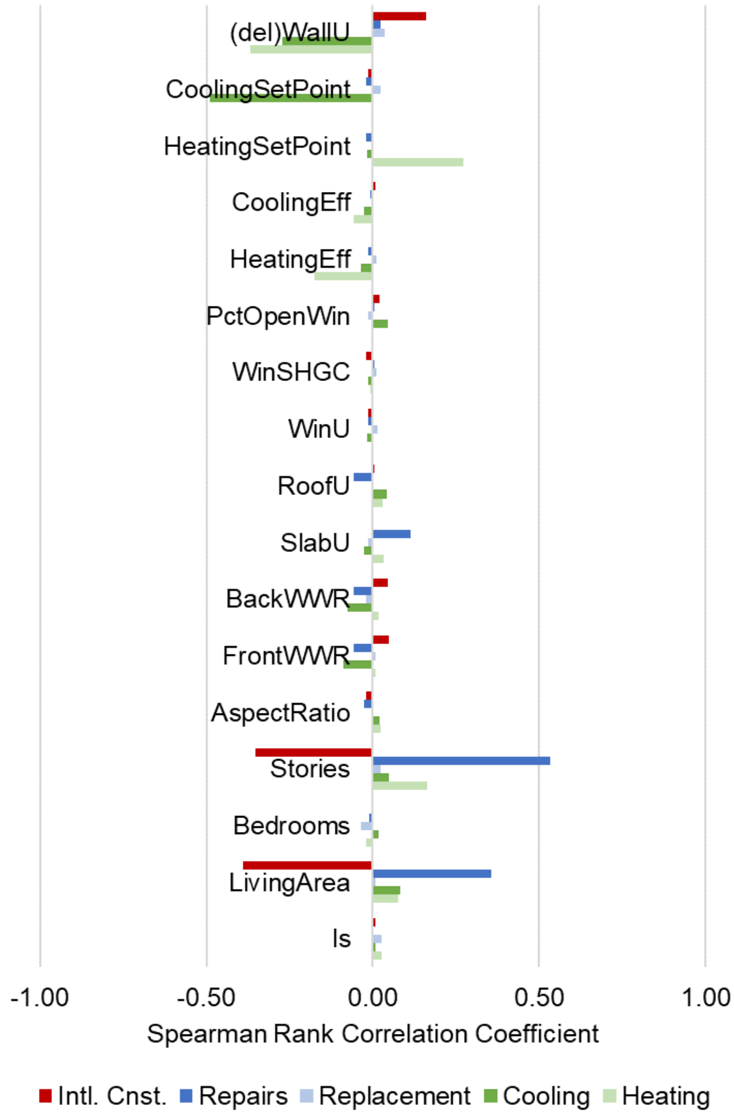

Figure 4.7-5. Spearman rank correlation between the difference in building stage emissions for wood versus concrete archetypes and continuous inputs; initial construction, repair, and replacement emissions exclude end-of-life emissions for the respective activity; figure shows inputs with at least one coefficient larger than .1 or less than -.1.

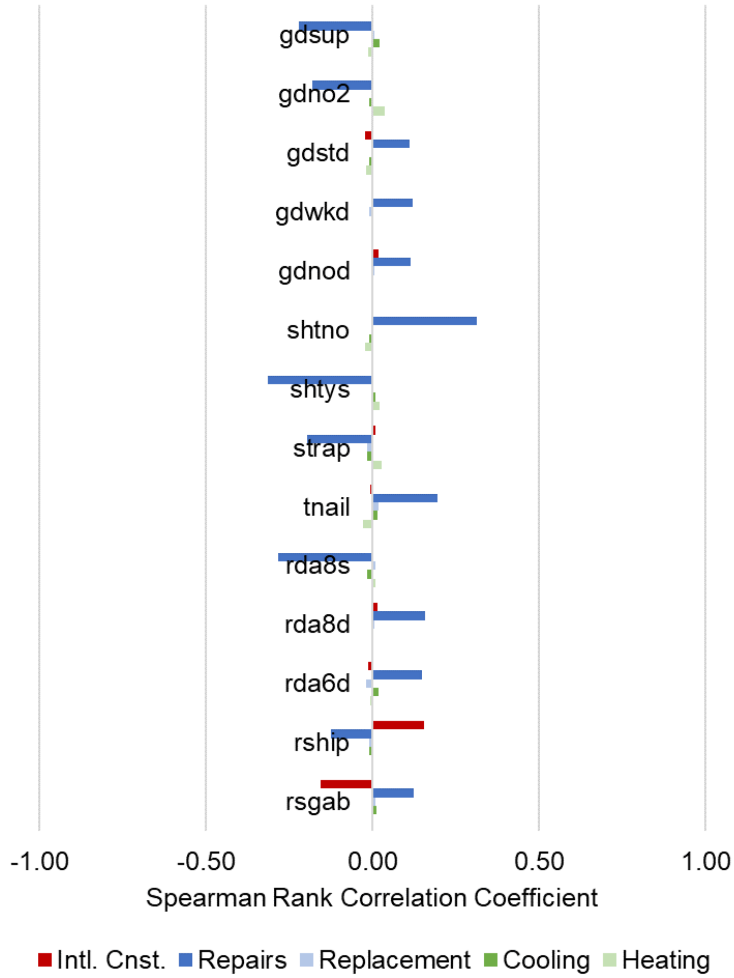

Figure 4.7-6. Spearman rank correlation between the difference in building stage emissions for wood versus concrete archetypes and categorical inputs; initial construction, repair, and replacement emissions exclude end-of-life emissions for the respective activity; figure shows inputs with at least one coefficient larger than .1 or less than -.1.

Mapping Exterior Wall Core Material Choice Recommendations

Here, we expand on building life cycle emissions from the previous section to derive exterior wall core material choice recommendations. **Figure 4.7-7** shows results of the comparative study for Miami-Dade, FL. **Figure 4.7-8** shows the same for the entire state. These maps are based on the 95th-percentile scenario of wind loading for each actualization. Both maps correspond to the same legend, where pink-orange tones indicate Census Tracts where concrete is the most eco-friendly option, while blue-green tones indicate Census Tracts where wood is the most eco-friendly option. Concrete, masonry, and wood homes are ranked based on building life cycle emissions. In Census Tracts where the ranking between two or more options is not statistically defensible, these options are noted as ‘tying’.

As discussed in the previous section, most studies of building embodied emissions only account for product (A1-3) and construction (A4-5) emissions. Hence, such studies would lead to recommendations as depicted on the left-side of **Figure 4.7-7**, as wood homes yield the lowest A-stage emissions.

In addition to product (A1-3) and construction (A4-5) emissions, this study accounts for repair (B3), replacement (B4), operational energy usage (B6), and end-of-life (C) emissions, as well as carbon uptake, capturing a more complete picture of building life cycle emissions. Our approach leads to recommendations as depicted on the right-side of **Figure 4.7-7** and in **Figure 4.7-8**.

These maps suggest that there is no one-size-fits-all solution, as concrete and masonry homes are favorable in more coastal and southern Census Tracts, where hurricane wind exposure is relatively higher, while wood homes are favorable in more inland and northern Census Tracts, where hurricane wind exposure is relatively lower. Therefore, assessing the outcomes of exterior wall core material choice is highly dependent on the climatological context.

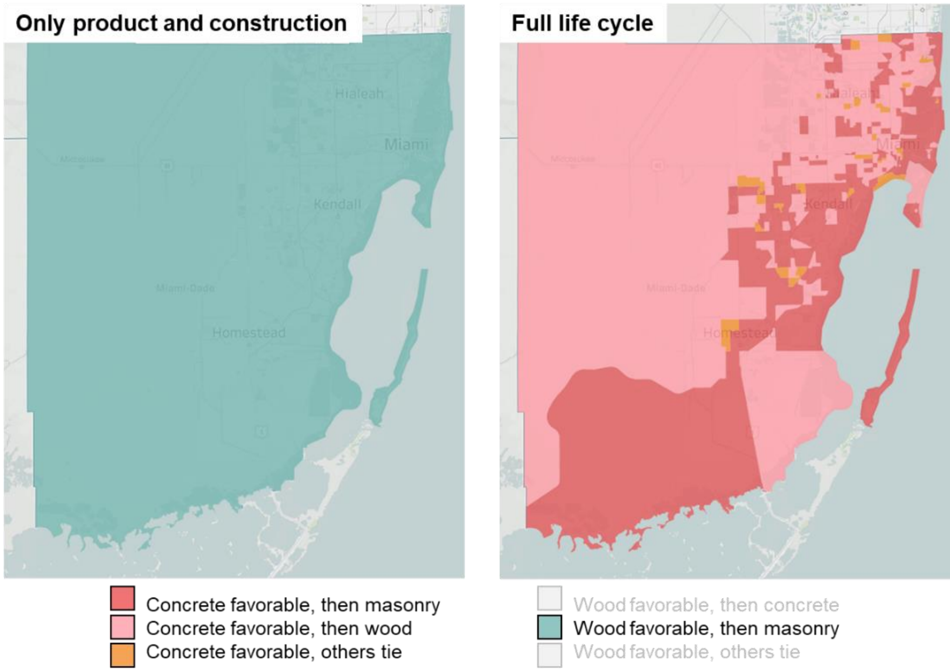

Figure 4.7-7. Exterior wall core material comparisons based on building life cycle emissions in Miami-Dade, FL; $p < .05$ across 5,000 actualizations, 95th-percentile scenario of 100 wind loading scenarios.

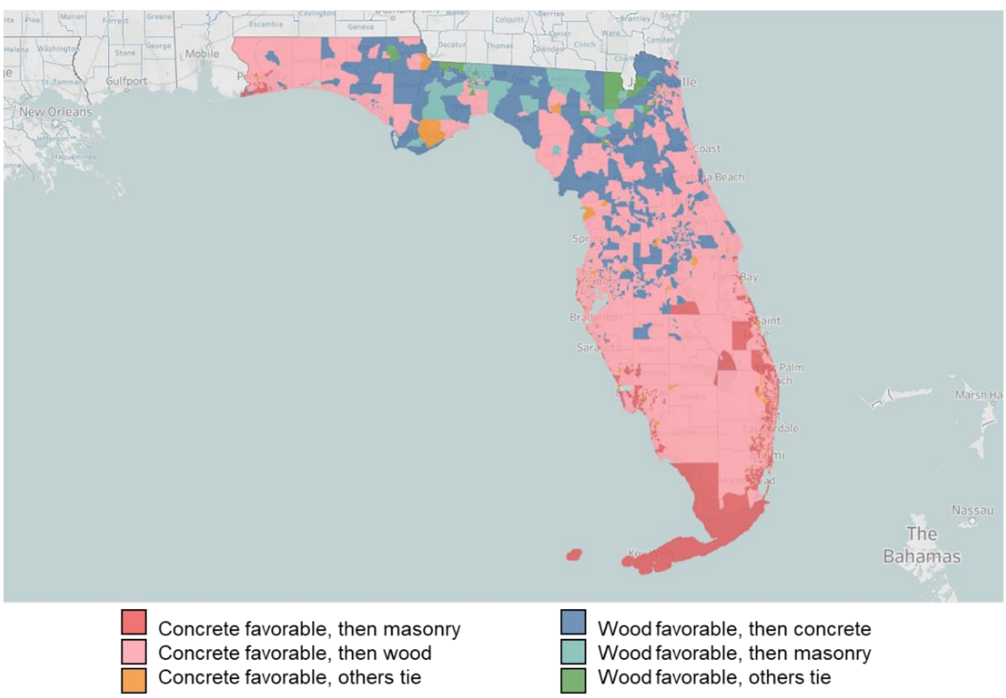

Figure 4.7-8. Exterior wall core material comparisons based on building life cycle emissions in Florida; $p < .05$ across 5,000 actualizations, 95th-percentile scenario of 100 wind loading scenarios.

4.8 Discussion

Present studies of building embodied emissions are mostly limited to the product and construction emissions associated with initial construction. However, this leads to a misleading assessment of which construction materials constitute ‘green’ buildings. Typically, this assessment is boiled down to an absolute preference between one construction material over the other (e.g. wood over concrete). In this manuscript, we demonstrate that a comprehensive assessment results in a ‘mix of fixes’ highly dependent on the climatological context.

We expand building embodied emissions to incorporate hazard vulnerability and carbon uptake, and then combine embodied emissions with operational energy usage emission to capture a full life cycle of emissions associated with the outcomes of construction material choice. A durable, hazard-resilient material like concrete may increase emissions associated with initial construction, but lower life cycle emissions by saving repair and replacement demands.

Particularly in hurricane-prone communities, hazard repair emissions can comprise a similar order of magnitude as initial construction emissions. Regarding exterior wall core material choice, we found that concrete is the favorable material option in more coastal and southern communities, where hurricane wind exposure is relatively higher and the hazard repair stage is the dominating factor, while wood is the favorable material option in more inland and northern communities, where hurricane wind exposure is relatively lower and the initial construction stage is the dominating factor. The favorability of concrete is particularly pronounced for large structures (greater living area, more stories) and/or structures lacking hurricane mitigation measures.

Ultimately, exterior wall core material choice is one of many decisions around building sustainability and hazard resilience. Future studies can extend this work to explore the outcomes of other decisions, such as selecting a different configuration of building characteristics like in **Table 4.5-1** and **Table 4.5-2**. These studies can also focus on a wider range of residential and commercial building archetypes, as well as a wider range of natural hazards, as archetypes respond to natural hazards in different ways.

4.9 Data Availability Statement

All data, models, or code generated or used during the study are available for the corresponding author by request.

4.10 Acknowledgements

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4.11 Declaration of Interest Statement

The authors report there are no competing interests to declare.

4.12 References

References can be found at the end of this work.

5 Contributions to Environmental Assessment: Sector Level

This chapter includes the manuscript "Exploring Opportunities for Building Life Cycle Assessment to Inform Cement Scope 1-3 Greenhouse Gas Accounting" authored by Ipek Bensu Manav, Hessam Azarijafari, and Randolph Kirchain. The title and content of the manuscript may have changed during peer review and publication.

5.1 Abstract

Present protocols for greenhouse gas (GHG) accounting imply that the full scope of cement's sectoral emissions cannot be captured. Based on cement's status as an intermediate product, these protocols assert that necessary information (e.g. design details) is lacking to measure or model cement's downstream emissions (e.g. use and end-of-life emissions of end-use applications such as buildings).

Previous work developed streamlined tools for building life cycle assessment (LCA) and loss estimation. This research allows us to estimate the full life cycle of a given building's GHG emissions while making use of very little or no additional design details. Combined with housing stock analysis and cement market share information, this research is extended to create a more complete picture of cement's sectoral environmental footprint (SEF) associated with buildings.

Particularly for long-life products like cement-based products (CBPs), ignoring downstream emissions can mean ignoring a large portion of their value chain. Model results show that scope 1-2 emissions comprise 26% of reportable building emissions, upstream scope 3 emissions comprise another 2%, while downstream scope 3 emissions comprise the remainder and majority

72%. Moreover, the largest portion of downstream scope 3 emissions derive from building operational energy usage.

This manuscript explores opportunities for building LCA to inform cement's SEF, especially throughout defining and estimating emission categories currently deemed too complex to tackle. Compared to present protocols, this exploration offers a broader range of pathways for the cement sector to strategize efforts for GHG reduction and neutralization.

5.2 Keywords

Life Cycle Assessment, Greenhouse Gas Reporting, Cement

5.3 Introduction

As an increasing number of countries, communities, and industry commit to lowering planetary greenhouse gas (GHG) emissions, organizations (e.g. companies) have a growing need for clear guidelines on setting and tracking targets for GHG abatement (IPCC, 2022). The current best practice for doing so is called organizational GHG accounting (and reporting) (GHGP, 2011, 2015).

Present protocols for organizational GHG accounting define three scopes of an organization's environmental footprint: scope 1 or direct emissions, scope 2 or indirect emissions associated with generation of purchased electricity, and scope 3 or any other indirect emissions upstream or downstream of the organization's direct activities.

The definition of scope 3 emissions is broad, and its emission categories are comprehensive, as this scope includes 15 emission categories spanning activities from the extraction of raw materials for production of the organization's product to the processing of wastes at the end-of-life of the organization's product. However, for materials producers, and particularly producers of intermediate goods, several of these emission categories are deemed "too difficult" to measure (WBCSD, 2011a). An example of such intermediate goods is cement, which gets mixed into cement-based products (CBPs) (e.g. ready-mixed concrete), which in turn gets cast into end-use applications (e.g. buildings). Cement producers often lack complete information on their product's end-use applications (e.g. specific operational energy usage of each building including CBPs). Because of this, present protocols rule out most downstream scope 3 emission categories for cement producers based on cement's status as an intermediate good (WBCSD, 2011a).

In this manuscript, our objective is two-fold. First, we extend organizational GHG accounting to study the full scope of reportable building emissions associated with the cement sector—as a whole, rather than focusing on a specific cement producer. While doing so, we define the sectoral environmental footprint (SEF) to encompass a good's scope 1-3 GHG emissions. Measuring and tracking cement's SEF is crucial to ongoing carbon-neutrality efforts, as an increasing number of commitments are made on industrial sector level (Battelle, 2002; WBCSD, 2002), as well as on national or regional level, where GHG emissions are aggregated on industrial sector level (EPA, 2023).

Second, we amend present protocols to offer ways in which building life cycle assessment (LCA) can supplement GHG accounting for emissions categories currently ruled out for being too complex to tackle. We demonstrate this integration with a focus on single-family dwellings. Combined with housing stock analysis and cement market share information, building LCA allows to model downstream emissions associated with the construction, use, and end-of-life of single-family dwellings including CBPs.

5.4 Literature Review

Organizational GHG accounting for cement producers is governed by initiatives from three international organizations: [1] Science-Based Targets Initiative's (SBTi's) cement guidance for target setting (SBTi, 2022), [2] World Business Council for Sustainable Development's (WBCSD's) cement guidance for GHG reporting (WBCSD, 2011b, 2011a), and [3] Greenhouse Gas Protocol (GHGP), the underlying protocols which define scopes and categories of GHG emissions (GHGP, 2011, 2015). A complete list of emission categories covered by GHGP and WBCSD can be found in the **Supplementary Materials**.

For the purposes of this study, we assume scope 1 activities include clinker production, yet exclude any other blending, grinding, bagging, or T&D beyond the factory gate. There are a variety of cement producers. Blending, grinding, and vertically-integrated plants differ based on their material intake, where blending and grinding plants purchase clinker, while vertically-integrated plants produce their own (WBCSD, 2011b). Cement producers also differ based on the reach of their transportation and distribution (T&D) network, as their final node can be the factory gate, other plants, or construction sites (WBCSD, 2011b).

Limiting scope 1 activities to clinker production simplifies our system boundaries, while making sure that we cover the single-most carbon-intensive process in cement manufacturing (i.e. clinker production), as well as the only process cement producers are required to report on (i.e. clinker production) regardless of whether they purchase clinker or produce their own (WBCSD, 2011b). Within our system boundaries, scope 1 emissions refer to direct emissions associated with clinker production, scope 2 emissions refer to indirect emissions associated with combustion of fuels for generation of purchased electricity, and scope 3 emissions refer to any other indirect emissions upstream or downstream of clinker production or generation of purchased electricity.

Scope 1 activities required to be reported on include calcination and combustion of raw materials and on-site combustion of fuels (WBCSD, 2011b). These fuels include those burned for kiln and non-kiln activities, on-site power generation, and on-site transportation involving internal combustion engine vehicles (ICEVs).

Scope 2 activities required to be reported on include off-site combustion of fuels for generation of purchased electricity (WBCSD, 2011b). This purchased electricity includes that consumed for kiln and non-kiln activities, on-site power generation, and on-site transportation involving electrical vehicles (EVs).

Upstream scope 3 activities required to be reported on include cradle-to-gate and T&D activities associated with purchased goods, services, and fuels (burned in scope 1 or 2) (WBCSD, 2011a). Though optional to report, these activities can include cradle-to-gate and T&D activities associated with capital goods (WBCSD, 2011a). The tricky part about accounting for capital goods emissions is allocation (i.e. deciding which portion of emissions to attribute to a given type or amount of product). However, life cycle inventories (LCIs) readily account for and thoroughly document allocation principles for capital goods emissions (ecoinvent, n.d.).

The only downstream scope 3 activities required to be reported on are T&D activities associated with sold goods (WBCSD, 2011a). Though optional to report, these activities can include activities associated with processing cement into CBPs, installing CBPs in buildings, and use and end-of-life of buildings (WBCSD, 2011a). As described earlier, these latter activities are deemed "too difficult" to measure or model for cement producers.

Typically, scope 1 activities are the easiest to report on, since they only involve the reporting party, while scope 2 and 3 are harder because they rely on collecting data from other partnering parties. Industrial ecology provides a versatile toolkit to aid various emission categories likely to experience data gaps (de Bortoli et al., 2023). This toolkit includes: LCIs and LCA.

LCIs can supplement scope 2 and upstream scope 3 accounting, as they offer an inventory of cradle-to-gate environmental impacts (e.g. GHG emissions) associated with a unit of direct activity (e.g. a kg of clinker production) (ecoinvent, 2021c). These environmental impacts include those associated with direct activity as well as upstream activities (e.g. cradle-to-gate and T&D activities associated with limestone used for a kg of clinker production). LCIs are easily accessible and thoroughly documented, however their estimates are based on industry averages and limited in geographic scope. These estimates need to be adjusted to account for local variability in technology, electrical grid, and material availability (Hottle et al., 2022; Klee et al., 2011).

In addition to the benefits of LCIs, LCA can supplement downstream scope 3 accounting, as it captures the full life cycle of environmental impacts associated with a product (e.g. a kg of cement). Relevant fields of study include organizational LCA (or O-LCA), LCA of cement, and LCA of buildings.

Similar to GHG accounting, the objective of O-LCA is to aid organizations in evaluating strategies for GHG abatement. The main difference between the practices is how they break down activities, as GHG accounting categorizes activities based on scopes, while O-LCA categorizes activities based on life cycle stages. Though O-LCA practitioners strongly urge organizations to consider downstream environmental impacts, a recent study found pushback from materials (and construction) sectors, as materials producers (and contractors) do not have full control over the final product that is buildings (and infrastructure) (Martínez-Blanco et al., 2020). Another study found similar pushback, adding a reason for the reluctance being that reported emissions seem higher when considering downstream environmental impacts (de Bortoli et al., 2023). However, different scopes are reported separately (WBCSD, 2011b, 2011a) and, often times, different scopes are assigned different GHG abatement targets (more ambitious for direct emissions) (SBTi, 2022). Thus, having a more comprehensive assessment of downstream scope 3 emissions does not interfere with ongoing efforts, yet presents new pathways to innovate to achieve targets.

LCA studies of cement explore methods to quantify the environmental impacts of cement. A number of these studies focus on mix design: substituting ordinary portland cement (OPC) with portland pozzolana cement (PPC) (Manjunatha et al., 2021), blast furnace slag (a side product of steel production) (Manjunatha et al., 2021), or fly ash (a side product of coal combustion) (Seto et al., 2017). Other studies consider a broader range of strategies for GHG abatement: recycling of cement kiln dust (CKD) (Huntzinger & Eatmon, 2009), improving energy efficiency (Busch et al., 2022), switching to alternative fuels (Busch et al., 2022; Salas et al., 2016), or implementing carbon capture utilization and storage (CCUS) (Busch et al., 2022; Salas et al., 2016). A few studies consider the potential of carbon uptake to contribute to GHG abatement (Busch et al., 2022; García-Segura et al., 2014). All of these studies have a cradle-to-gate cut-off (apart from those which consider carbon uptake), ignoring environmental impacts beyond the factory gate (apart from carbon uptake) (Ige et al., 2021).

Lastly, LCA studies of buildings explore methods to quantify the environmental impacts of entire (or parts of) buildings (including the environmental impacts of cement, or CBPs, consumed in building construction). The building life cycle consists of product (A1-3), construction (A4-5), use (B), and end-of-life (C) stages. Present studies look at emissions associated with a variety of combinations of these stages (Pomponi & Moncaster, 2016). Considering the breadth of emission categories covered by GHGP, a portion of emissions in each of these stages is relevant to at least one of the scopes within cement's SEF. However, no study to date has mapped the connection between building life cycle emissions and cement's SEF (or the SEF of any other construction material).

In this manuscript, we explore opportunities for building LCA to inform cement's SEF. In **Chapter 4** of this work, we propose an integrated building LCA framework to assess the regional influence of hazard vulnerability on life cycle emissions associated with single-family dwellings. To do this, we make use of streamlined LCA, loss estimation, and housing stock analysis. In this manuscript, we combine this framework with cement market share information to estimate the contribution of single-family dwellings to cement's SEF over the years.

5.5 Methodology

The objective of this study is to estimate the contribution of single-family dwellings to cement's SEF over the years. As described earlier, scope 1 emissions are direct emissions associated with clinker production, scope 2 emissions are indirect emissions associated with combustion of fuels for generation of purchased electricity, and scope 3 emissions are any other indirect emissions upstream or downstream of clinker production or generation of purchased electricity.

In this context, cement is the intermediate good, CBPs are the primary good, and single-family dwellings are the final product. Upstream scope 3 includes cradle-to-gate and T&D activities associated with purchased goods, services, fuels, and capital goods used in either clinker production (scope 1) or generation of purchased electricity (scope 2). Downstream scope 3 includes activities associated with processing clinker into CBPs, as well as the construction, use, and end-of-life of buildings.

Present protocols rule out several of these activities within emission categories on the basis that they are "too complex" to measure or model (WBCSD, 2011b, 2011a). To measure them, we would need to gauge every electrical grid, smokestack, tailpipe, and chimney, and add up respective emissions. The costs of such an operation would be astronomical. To model them, ideally, we would analyze a dataset of every home permitted to be built in each year, where all building characteristics are known. However, in the U.S., not all characteristics are tracked, while others are found across several datasets aggregated on various levels at much less granular scales (e.g. Census Division).

In this manuscript, we offer opportunities to aid reporting a full scope of emissions while making use of data and models that are currently available and publicly accessible. In doing so, we evaluate life cycle emissions for each building b built in each year. Our methodology consists of four aspects: [1] identifying which building life cycle emissions map onto cement's SEF, [2] evaluating life cycle emissions for building archetypes, [3] defining 'excess' energy usage, and [4] scaling LCA results to study cement's SEF over the years.

Identifying Which Building Life Cycle Emissions Map onto Cement's SEF

The life cycle emissions associated with each building b consist of embodied and operational emissions. Formally, that is

$$LC_b = Ed_b + Ol_b \qquad \text{Eq.4.5.1}$$

where LC_b is the life cycle emissions of b, Ed_b is its embodied emissions, and Ol_b is its operational emissions.

Embodied emissions relate to product, construction, and end-of-life emissions associated with material consumption. Operational emissions relate to fuels and electricity emissions associated with operational energy usage.

To identify which building embodied emissions map onto cement's SEF, we first need to identify which CBPs are used in building components. In the context of single-family dwellings, a variety of CBPs can be used in a variety of building components. A complete list of building components considered can be found in **Table 5.5-1** and a complete list of CBPs considered can be found in **Table 5.5-2**. For instance, cast-in-place concrete can be used in exterior walls, slab foundations, or footings, while concrete masonry units (CMUs) can be used in exterior walls or basement walls.

To evaluate the reportable embodied emissions arising from each b, we first evaluate embodied emissions arising from each CBP used in each building component found in b. That is

$$SEF_b^{Ed} = \sum_{cbp \in bc} \sum_{bc \in b} Ed_{cbp,bc} \quad \text{Eq.4.5.2}$$

where SEF_b^{Ed} is the reportable embodied emissions of b and $Ed_{cbp,bc}$ is the embodied emissions associated with CBP cbp used in building component bc found in b.

Embodied emissions arising from each CBP consists of ‘direct’ and ‘indirect’ emissions. As discussed earlier, we simplify our system boundaries by limiting direct activities to clinker production (scope 1). These direct activities consist of kiln and non-kiln activities. A complete list of kiln activities considered can be found in **Table 5.5-3** and a complete list of non-kiln activities considered can be found in **Table 5.5-4**.

Present protocols require cement producers to report a selection of indirect activities as well. These required indirect activities include generation of purchased electricity (scope 2), cradle-to-gate and upstream T&D activities associated with purchased goods, services, and fuels (upstream scope 3), and downstream T&D activities associated with sold goods (downstream scope 3) (WBCSD, 2011a). We extend required upstream activities to include cradle-to-gate and T&D activities associated with capital goods, which we allocate based on information found in LCIs (ecoinvent, 2021c). This is one of our contributions, however the majority of our contributions are in our treatment of downstream activities.

We extend required downstream activities to include activities associated with processing clinker into CBPs, as well as the construction, use, and end-of-life activities of buildings. The former consists of T&D activities of delivering clinker to the processing site, ‘direct’ activities associated with CBP production, and cradle-to-gate and T&D activities associated with other (non-clinker) goods, services, fuels, and capital goods used in CBP production. The latter consists of T&D activities of delivering CBPs to the construction site, 'direct' activities associated with building construction, use, and end-of-life, and carbon uptake (a chemical process inherent to CBPs which leads to negative emissions during building construction, use, and end-of-life).

The use of buildings leads to operational emissions, in addition to embodied emissions discussed thus far. In this work, reportable building emissions account for a portion of emissions associated with building operational energy usage. We call this portion 'excess' (defined later).

Although all stages of the building life cycle are relevant to cement's value chain, we only account for a portion of emissions associated with each building life cycle stage in cement's SEF. A complete list of building life cycle emissions considered in cement's SEF can be found in **Table 5.5-5**. This is also shown in **Figure 5.5-1**. Specifically, we assume product, construction, and end-of-life emissions associated with CBPs used in initial construction, repair, and replacement are *in scope*, while the same for other (non-CBP) goods are *out of scope*.

In reality, a multitude of stakeholders are involved in upstream and downstream activities. Each such activity contributes to a unique stakeholder's scope 1 emissions, while also contributing to the scope 2 or 3 emissions of the other stakeholders. A tentative list of stakeholders in cement's value chain can be found in the **Supplementary Materials**. For instance, the scope 1 emissions of a coal plant are the scope 2 emissions for a cement plant, the scope 1 emissions of a limestone quarry are upstream scope 3 emissions for the cement plant, and the scope 1 emissions of a ready-mixed concrete plant are downstream scope 3 emissions for the cement plant. In this work, we are not interested in identifying individual stakeholders so much as creating a comprehensive understanding of activities within cement's value chain. (Reserved for future studies, this understanding can be applied to other residential and commercial building archetypes, not just single-family dwellings.)

Evaluating Life Cycle Emissions for Building Archetypes

As formalized in **Eq.4.5.1**, the life cycle emissions associated with each building b consist of embodied and operational emissions. The embodied component of building life cycle emissions includes emissions associated with materials consumed in initial construction, repair, and replacement. That is

$$Ed_b = IC_b + Rr_b + Rt_b \qquad \text{Eq.4.5.3}$$

where Ed_b is the embodied emissions of b, IC_b is its initial construction emissions, Rr_b is its hazard repair emissions, and Rt_b is its replacement emissions.

We use the terms 'initial construction', 'repair', and 'replacement' to refer to the sum of life cycle activities associated with a stream of material consumption. Hence, initial construction, repair, and replacement emissions, each, include relevant product, construction, and end-of-life emissions. Together, that is

$$X_b = P_{x,b} + C_{x,b} + EoL_{x,b} + CU_{x,b} \qquad \text{Eq.4.5.4}$$

where X_b is the emissions of X (initial construction, repair, or replacement) of b, $P_{x,b}$ is its product emissions, $C_{x,b}$ is its construction emissions, $EoL_{x,b}$ is its end-of-life emissions, and $CU_{x,b}$ is its carbon uptake associated with CBPs consumed.

The operational component of building life cycle emissions includes emissions associated with fuels and energy consumed for operational energy usage. That is

$$Ol_b = EU_b \qquad \text{Eq.4.5.5}$$

where Ol_b is the operational emissions of b and EU_b is its operational energy usage emissions.

In **Chapter 4** of this work, we create building archetypes to represent building characteristics pertinent to evaluating embodied and operational emissions. These building archetypes differ based on: exterior wall core material (concrete, masonry, or wood), number of stories (1, 2, or 3), living area (small, medium, or large), roof shape (gable or hip), roof cover (asphalt shingles, concrete tiles, or metal cladding), window area (low, medium, or high), among several other building characteristics. Along with locational characteristics (e.g. climate), these building characteristics help estimate material and energy demands.

Building geometry and material definitions directly impact material demands for initial construction, while other material and energy demands rely heavily on locational characteristics. This is reflected in a number of effects. Exposure to natural hazards (e.g. hurricane winds) leads to higher hazard repair demands. Humidity leads to higher replacement demands (more regular wear-and-tear). Humidity also inhibits carbon uptake on outdoor surfaces. Temperature affects heating and cooling demands. Material definitions amplify or reduce these effects, as more durable, hazard-resilient materials require less repair and replacement, and massive materials cut down on heating and cooling.

In this manuscript, we apply the integrated building LCA and loss estimation framework presented in a recent manuscript. This framework uses a combination of building archetypes to evaluate emissions associated with the construction, use, and end-of-life of typical single-family dwellings in a region. To reiterate, we do not account for the entirety of building life cycle emissions in cement's SEF, but a portion, including embodied emissions associated with CBPs and operational emissions associated with 'excess' energy usage (as shown in **Figure 5.5-1**).

Defining 'Excess' Energy Usage

Although present protocols recognize emissions associated with building operational energy usage as part of downstream emissions, they lack clear guidelines (or even a precedent) regarding what portion of building operational energy usage to account for. Operational energy usage of each building b consists of fuels and electricity used for heating, cooling, and other purposes such as lighting and appliances. That is

$$EU_b = Hg_b + Cg_b + Or_b \qquad \text{Eq.4.5.6}$$

where EU_b is the operational energy usage emissions of b, Hg_b is its heating emissions, Cg_b is its cooling emissions, and Or_b is its other operational energy usage emissions.

To achieve both 'completeness' and 'relevance' principles in GHG accounting (GHGP, 2015), we make two recommendations: [1] limit reporting to building heating and cooling, and [2] apply a science-based metric to identify CBPs' contribution to building heating and cooling performance.

Regarding [1], CBPs are used in building components (e.g. exterior wall core) which impact building heating and cooling performance (e.g. thermal resistance, or its inverse thermal conductivity). However, they are not used in any building components which impact building operational energy usage associated with other purposes. Thus, only heating and cooling is relevant to report on within cement's SEF. This can be shown as

$$SEF_b^{OI} \propto Hg_b + Cg_b \qquad \text{Eq.4.5.7}$$

where SEF_b^{OI} is the reportable operational emissions associated with b, Hg_b is its heating emissions, and Cg_b is its cooling emissions.

Regarding [2], building façade, roof, and foundation all contribute to building heating and cooling performance, but building façade by far is the most influential. Building façade consists of windows, exterior doors, and exterior walls, while exterior walls consist of exterior wall core and exterior and interior finishings.

Windows, exterior doors, and exterior walls represent a system in parallel (as shown in **Figure 5.5-2**). Based on principles of heat transfer, these building components contribute to a combined thermal conductivity proportional to their individual thermal conductivities and surface areas. This leads to the relationship

$$U_b SA_b = U_b^{window} SA_b^{window} + U_b^{door} SA_b^{door} + U_b^{wall} SA_b^{wall} \qquad \text{Eq.4.5.8}$$

where U_b is the combined thermal conductivity of b, U_b^{wall} is that of its windows, U_b^{doors} is that of its exterior doors, and U_b^{wall} is that of its exterior walls, and SA_b is the total surface area comprising of SA_b^{walls} the surface area of windows, SA_b^{door} the surface area of exterior doors, and SA_b^{walls} the surface area of exterior walls.

Hence, the contribution of CBPs in exterior walls to heating and cooling performance is inversely proportional to the thermal conductivity and surface area of exterior walls, compared to other façade component buildings, shown as

$$SEF_b^{OI} \propto CBP_b^{walls} (U_b^{walls} SA_b^{walls})^{-1} \qquad \text{Eq.4.5.9}$$

where SEF_b^{OI} is the reportable operational emissions associated with b, CBP_b^{walls} is the indicator of whether its exterior walls include CBPs, U_b^{wall} is the thermal conductivity of its exterior walls, and SA_b^{walls} is its surface area.

Exterior wall core and exterior and interior finishings represent a system in series (as shown in **Figure 5.5-2**). Based on principles of heat transfer, these building components contribute to a combined thermal conductivity inversely proportional to their individual thermal conductivities (area is not a factor since it is the same). This leads to the relationship

$$(U_b^{walls})^{-1} = (U_b^{EWC})^{-1} + (U_b^{EF})^{-1} + (U_b^{IF})^{-1} \qquad \text{Eq.4.5.10}$$

where U_b^{walls} is the thermal conductivity of b's exterior walls, U_b^{EWC} is that of its exterior wall core, U_b^{EF} is that of its exterior finishing, and U_b^{IF} is that of its interior finishing.

Apportioning building heating and cooling comes down to layers in exterior wall core. Exterior and interior finishings contribute to thermal resistance negligibly (if at all) (Hester, 2018). Thus, we remove them from the equation. Exterior wall core itself consists of multiple layers. Depending on the exterior wall core material, these layers include insulation (rigid or nonrigid), wood products (e.g. sheathing), and CBPs. This can be denoted as

$$(U_b^{EWC})^{-1} = \sum_{l \in EWC} (U_b^{l})^{-1} \qquad \text{Eq.4.5.11}$$

where U_b^{EWC} is the thermal conductivity of b's exterior wall core and U_b^{l} is that of its exterior wall core layers.

Hence, the contribution of CBPs in exterior wall core to heating and cooling is proportional to the thermal conductivity of CBP layer, compared to other layers in exterior wall core, shown as

$$SEF_b^{Ol} \propto \sum_{l \in EWC} CBP_b^l U_b^l \qquad \text{Eq.4.5.12}$$

where SEF_b^{Ol} is the reportable operational emissions associated with b, CBP_b^l is the indicator of whether its exterior wall core layers include CBPs , and U_b^l is the thermal conductivity of its exterior wall core layers.

Considering the relationships in **Eq.4.5.7**, **Eq.4.5.9**, and **Eq.4.5.12**, reportable operational emissions arising from each b is represented by its heating and cooling apportioned proportional to the contribution of CBPs to exterior wall core thermal conductivity and inversely proportional to the contribution of exterior walls to façade thermal conductivity. 'Excess' energy usage is defined to capture the impacts of CBPs on building operational energy usage.

Scaling LCA Results to Study Cement's SEF Over the Years

To scale building LCA results, we first aggregate the number of single-family dwellings built in each year. That is

$$N_t = \sum_{ba} N_{ba,t} \qquad \text{Eq.4.5.13}$$

where N_t is the number of single-family dwellings built in analysis year t and $N_{ba,t}$ is that of its building archetypes. For N_t, we refer to the U.S. Census Bureau's Building Permits Survey (BPS) (U.S. Census Bureau, 2020b). For $N_{ba,t}$, we make use of building characteristic information from the U.S. Census Bureau's American Housing Survey (AHS) (U.S. Census Bureau, 2019) and the Federal Emergency Management Agency's (FEMA's) HAZUS model database (FEMA, 2021b).

To evaluate reportable building emissions in each year, we sum the reportable emissions associated with each building b of each building archetype built in each year. That is

$$SEF_t = \sum_{ba} \sum_{b \in ba} (SEF_b^{Ed} + SEF_b^{Ol}) \qquad \text{Eq.4.5.14}$$

where SEF_t is the reportable building emissions in analysis year t, SEF_b^{Ed} is the reportable embodied emissions associated with b as defined in **Eq.4.5.2**, and SEF_b^{Ol} is its reportable embodied emissions as defined across **Eq.4.5.7**, **Eq.4.5.9**, and **Eq.4.5.12**. The number of b s of each building archetype add up to $N_{ba,t}$ in each analysis year, and the total number of b add up to N_t .

To match our estimate of clinker consumed to the actual amount of clinker sold in each year, we apply a correction factor on reportable building emissions. This leads to the relationship

$$SEF_t^{corr} = \left(\frac{M_t^{corr}}{M_t} \right) SEF_t \qquad \text{Eq.4.5.15}$$

where SEF_t^{corr} is the corrected reportable building emissions in analysis year t, SEF_t is the *uncorrected* reportable building emissions, M_t is our estimate of clinker consumed, and M_t^{corr} is the actual amount sold. For this, we refer to clinker sales information from the Portland Cement Association (PCA).

To map reportable embodied emissions onto scopes and categories in cement's SEF, we need to break down LCI data into 'direct' and upstream portion, as LCI data incorporated into building LCA is based on cradle-to-gate emissions for primary materials (e.g. CBPs) which map onto a variety of scope 1, 2, and 3 categories in cement's SEF. LCI documentation helps separate 'direct' and upstream emissions. This varies by CBP. For instance, >90% of emissions associated with ready-mixed concrete production is upstream emissions associated with clinker production (ecoinvent, 2021a). Upstream emissions associated with clinker production also have cradle-to-gate cut-off. Hence, these emissions need to be further broken down (>90% ‘direct’ and <10% upstream) (ecoinvent, 2021c), as well as emissions associated with fuel and electricity production (>80% ‘direct’ and <20% upstream) (ecoinvent, 2021b).

For additional details on clinker production, we recommend referring to process models such as those derived from the U.S. Energy Information Agency’s (EIA’s) Manufacturing Energy Consumption Survey (MECS) (EIA, 2018). Process models are especially useful to discern sources of scope 1 emissions, particularly between emissions associated with calcination of raw materials versus combustion of fuels.

Table 5.5-1. List of building components considered (Hester, 2018).

Code	Description
BC1	Concrete tile roof
BC2	Brick exterior finishing (as mortaring)
BC3	Stone exterior finishing (as mortaring)
BC4	Masonry exterior wall core
BC5	Concrete exterior wall core
BC6	Precast concrete exterior wall core
BC7	Slab foundation
BC8	Foundation footings
BC9	Masonry basement walls

Note: BC1 (concrete tile roof) and BC6 (precast concrete exterior wall core) correspond to zero prevalence among single-family dwellings.

Table 5.5-2. List of CBPs considered (Hester, 2018).

Code	Description
CBP1	Concrete tile
CBP2	Mortaring
CBP4	Concrete masonry unit
CBP5	Concrete masonry unit filler
CBP6	Cast-in-place concrete
CBP7	Precast concrete

Note: CBP1 (concrete tile) and CBP7 (precast concrete) correspond to zero prevalence among single-family dwellings.

Table 5.5-3. List of kiln activities considered as part of clinker production (WBCSD, 2011b).

Code	Description
S1-1	Calcination of raw meal (e.g. limestone)
S1-2	Combustion of organic carbon
S1-3	Calcination of bypass dust
S1-4	Calcination of cement kiln dust
S1-5	Combustion of fossil fuels and biofuels

Table 5.5-4. List of non-kiln activities considered as part of clinker production (WBCSD, 2011b).

Code	Description
S1-6	On-site power generation (e.g. boilers)
S1-7	On-site transportation
S1-8	Off-site transportation
S1-9	Equipment
S1-10	Room heating and cooling
S1-11	Drying of mineral components

Table 5.5-5. Mapping building life cycle emissions onto cement's sectoral emissions.

Relevance to Cement Sector	Emissions	Required to Report?
In scope, indirect; contribute to upstream scope 3 emissions	**A1-2 and B2-5 <> upstream scope 3, categories 1, 3, and 4**; cradle-to-gate and T&D emissions associated with raw materials, fuels, and electricity used for clinker production	**Required by WBCSD**
	A1-2 and B2-5 <> upstream scope 3, categories 2 and 4; cradle-to-gate and T&D emissions associated with capital goods used for clinker production	NOT required by WBCSD because "insignificant"
In scope, direct; contribute to scope 1 emissions	**A1 and B2-5 <> scope 1**; scope 1 emissions associated with production of clinker used for CBPs	**Required by WBCSD**
In scope, indirect; contribute to scope 2 emissions	**A1 and B2-5 <> scope 2**; Scope 1 emissions associated with generation of purchased electricity for production of clinker used for CBPs	**Required by WBCSD**
In scope, indirect; contribute to downstream scope 3 emissions	**A2 and B2-5 <> downstream scope 3, category 9**; T&D emissions associated with clinker used for production of CBPs	**Required by WBCSD**
	A1-2 and B2-5 <> downstream scope 3, category 10; cradle-to-gate and T&D emissions associated with materials that are NOT clinker but used for production of CBPs	Not mentioned by WBCSD
	A3 and B2-5 <> downstream scope 3, category 10: scope 1-2 emissions associated with production of CBPs used for initial construction, repair, and replacement (including carbon uptake of cement wastage)	NOT required by WBCSD because "difficult"
	A4 and B2-5 <> downstream scope 3, category 10; T&D emissions associated with CBPs used for initial construction, repair, and replacement	Not mentioned by WBCSD
	A5 and B2-5 <> downstream scope 3, category 10; scope 1-2 emissions associated with installation of CBPs used for initial construction, repair, and replacement	NOT required by WBCSD because "difficult"
	B1 and B2-5 <> downstream scope 3, category 11; scope 1-2 emissions associated with use of CBPs used for initial construction, repair, and replacement (including carbon uptake)	
	B6-7 <> downstream scope 3, category 11; scope 1-2 emissions associated building 'excess' energy usage	
	C1-4 <> downstream scope 3, category 12; scope 1-2 emissions associated with end-of-life of CBPs used for initial construction, repair, and replacement (including carbon uptake)	
Out of scope	**A1-5, B2-5, and C1-4 <> out of scope**; Scope 1-3 emissions associated with non-CBP materials used for initial construction, repair, and replacement	Not mentioned by WBCSD

Note: T&D = transportation and distribution, CBP = cement-based product.

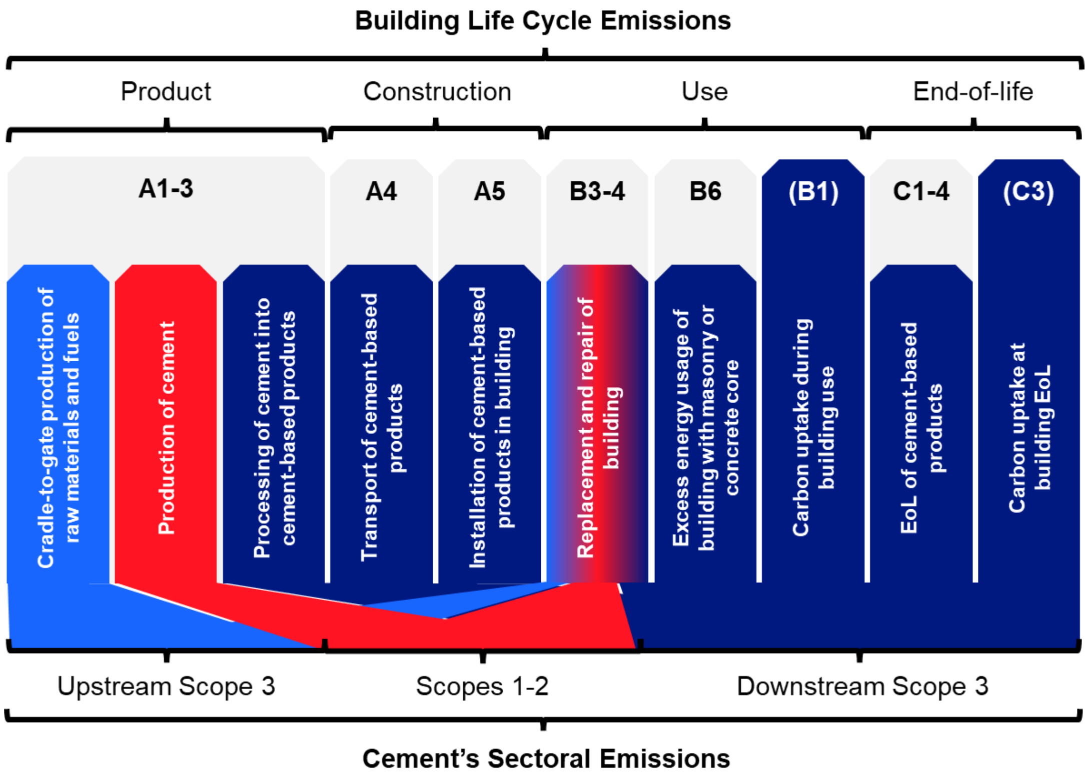

Figure 5.5-1. Outline of how building life cycle emissions map onto cement's sectoral emissions; all building life cycle stages relevant to cement's value chain, however only a portion of emissions in each building life cycle stage relevant to report in cement's sectoral emissions.

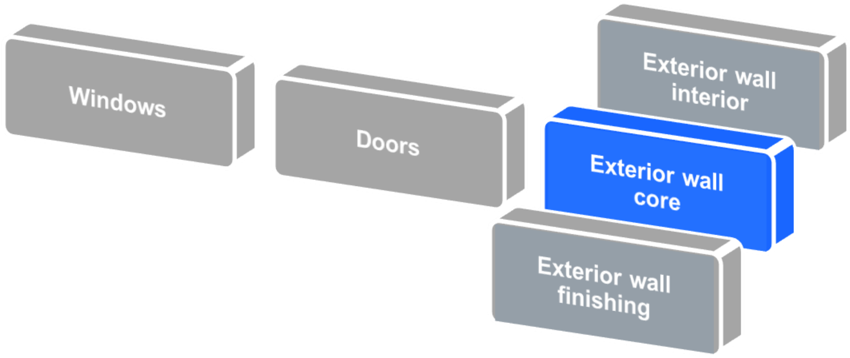

Figure 5.5-2. Building components in parallel and in series on building façade; windows, doors, and exterior wall in parallel, while exterior wall core in series with exterior and interior finishings.

5.6 Case Study

To explore opportunities for building LCA to inform cement's SEF, we applied the methodology described **Section 5.5** to analyze reportable emissions associated with single-family dwellings across the hurricane-prone state of Florida.

The analysis of Florida is based on information from the 2018 updates for the BAIA and HAZUS models, as well as 2018 AHS data. As described earlier, this information is aggregated on various levels.

To evaluate building life cycle emissions, we apply an integrated building LCA and loss estimation framework. Locational and building characteristic information is necessary for both LCA and loss estimation elements of this framework. Various pieces of this information are available on Census Tract, county, state, or regional level.

To estimate the number of single-family dwellings built in each year, we make use of BPS and PCA data. BPS building permits data is available for each county in the U.S. (U.S. Census Bureau, 2020b). Projects *permitted* are not necessarily projects *completed*, but building permits are publicly accessible, while specific project completion dates are typically kept private. To make up for this discrepancy, we match our estimate of clinker consumed to the actual amount of clinker sold. PCA clinker sales data is available for each state in the U.S. This data spans 1940 through 2018. Although AHS and BPS data span a broader timeframe, we select 1940 through 2018 as an analysis period to ensure we have a complete set of information for each state and analysis year.

5.7 Results

The objective of this case study is to map life cycle emissions associated with Florida single-family dwellings onto cement's SEF over an analysis period of 1940 through 2018. Our results consist of two parts: [1] evaluating building life cycle emissions for a year of added housing stock, and [2] estimating reportable emissions within cement's SEF for the entire analysis period.

Evaluating Building Life Cycle Emissions

In this section, we evaluate building life cycle emissions for Florida homes built in 2018. **Figure 5.7-1** shows building life cycle emissions for Florida homes built in 2018 and **Figure 5.7-2** shows only the portion of those building life cycle emissions which map onto cement's SEF (i.e. reportable emissions). Product and construction emissions for initial construction map onto cement's SEF in 2018, and other emissions map onto later years until every building in this added housing stock reaches the end of its service life.

As shown in **Figure 5.7-1**, operational energy usage emissions comprise the largest portion of building life cycle emissions. Product emissions for initial construction and repair emissions track a similar order of magnitude, particularly in Florida where homes are exposed to hurricane wind loading. In other states, with lower exposure to hurricane wind loading, repair emissions might be lower, or even on-par but driven by a different natural hazard (e.g. flooding or earthquakes).

As described earlier, all stages of the building life cycle are relevant to cement's value chain, however only a portion of emissions associated with each building life cycle stage falls within cement's SEF. Reportable embodied emissions are limited to product, construction, and end-of-life emissions associated with CBPs used in initial construction, repair, and replacement. As shown in **Figure 5.7-2**, reportable repair emissions are much lower than reportable product emissions for initial construction. This is because hazard repairs rarely occur in building components containing CBPs (e.g. foundations). (Further discussion of reportable embodied emissions can be found in the **Supplementary Materials**.)

'Excess' energy usage emissions comprise 20% to 50% of operational energy usage emissions (20% for concrete homes, 50% for masonry homes). Reportable operational emissions represent less than half of operational energy usage emissions. As shown in **Figure 5.7-2**, reportable operational emissions comprise more than half of reportable emissions. (Further discussion of reportable operational emissions can be found in the **Supplementary Materials**.)

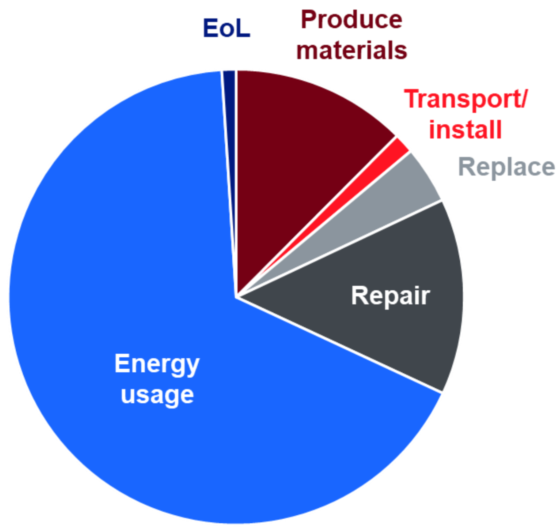

Figure 5.7-1. Breakdown of building life cycle emissions; Florida homes built in 2018.

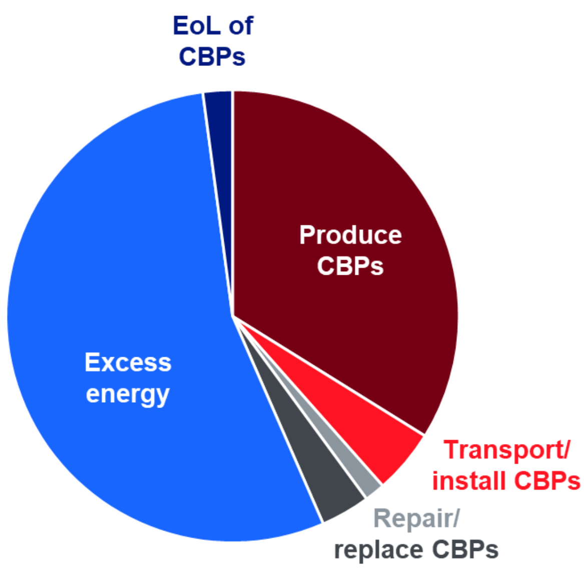

Figure 5.7-2. Breakdown of building life cycle emissions which map onto cement's sectoral emissions; Florida homes built in 2018.

Estimating Reportable Emissions within Cement's SEF

Here, we scale up reportable emissions associated with CBPs used in Florida homes built in 1940 through 2018 to capture cement's SEF over the years. **Figure 5.7-3** shows reportable emissions associated with CBPs used in Florida homes built in 1940 through 2018 and **Figure 5.7-4** shows a snapshot of these reportable emissions in 2018. Product and construction emissions for initial (i.e. new) construction in a given analysis year maps onto cement's SEF in that year, and other emissions map onto later years until every building in this added housing stock reaches the end of its service life.

Cement's SEF grows over time, not only because new construction rates go up, but because the existing housing stock grows, contributing to a larger number of homes creating operational energy usage emissions, or reaching the end of their service life and creating end-of-life emissions. Scope 1, 2, and upstream scope 3 emissions follow the trend of cement sales. While downstream scope 3 emissions follow the same trend, they also grow over time. As shown in **Figure 5.7-3**, in earlier analysis years, downstream scope 3 emissions comprise a smaller portion of reportable emissions. Towards the end of the analysis period, downstream scope 3 emissions comprise the largest portion of reportable emissions.

As shown in **Figure 5.7-4**, scope 1-2 comprise 26% of reportable emissions in 2018, upstream scope 3 comprises 3%, while downstream scope 3 comprises the remainder and majority 72%. The majority (>95%) of scope 1-2 emissions arise from calcination of raw materials (i.e. process emissions) and combustion of kiln fuels. The majority (>95%) of upstream scope 3 emissions arise from production of raw materials, fuels, and electricity. The majority (>99%) of downstream scope 3 emissions arise from construction, use, and end-of-life of buildings.

By the end of the analysis period, downstream scope 3 includes use and end-of-life emissions from housing stock added in 2017, 2016,… going all the way back to 1940 (the beginning of the analysis period). Consequently, similar to values shown in **Figure 5.7-3** and **Figure 5.7-4**, operational energy usage emissions comprise the largest portion of cement's SEF. However, distinct from values shown in **Figure 5.7-3** and **Figure 5.7-4**, end-of-life emissions comprise a larger portion of cement's SEF than they do in the full life cycle of housing stock added in a single year.

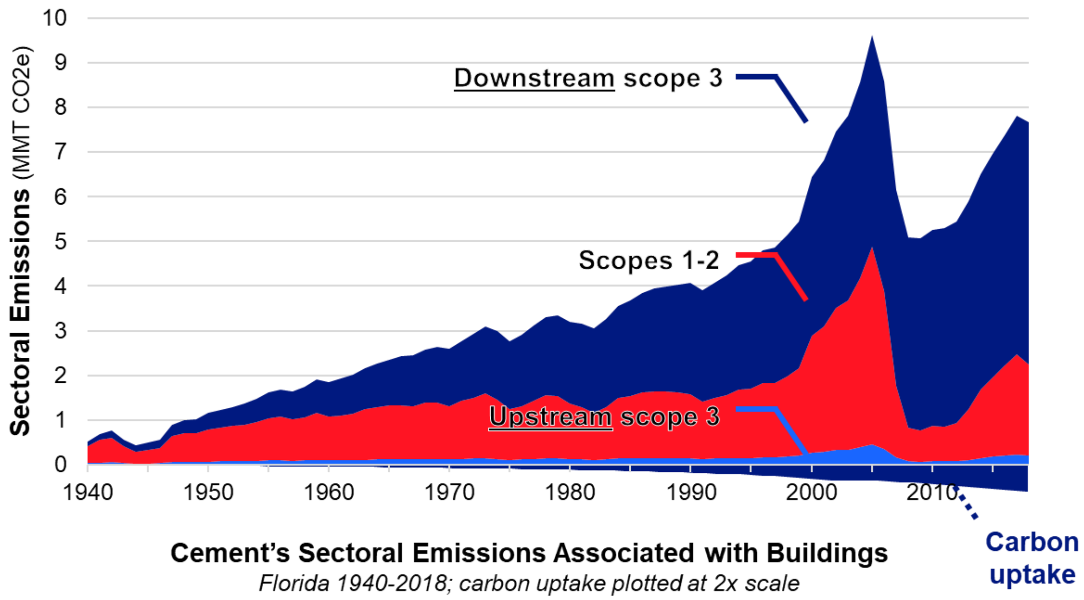

Figure 5.7-3. Reportable emissions associated with cement-based products used in Florida homes built in 1940-2018; carbon uptake plotted at 2x scale for readability.

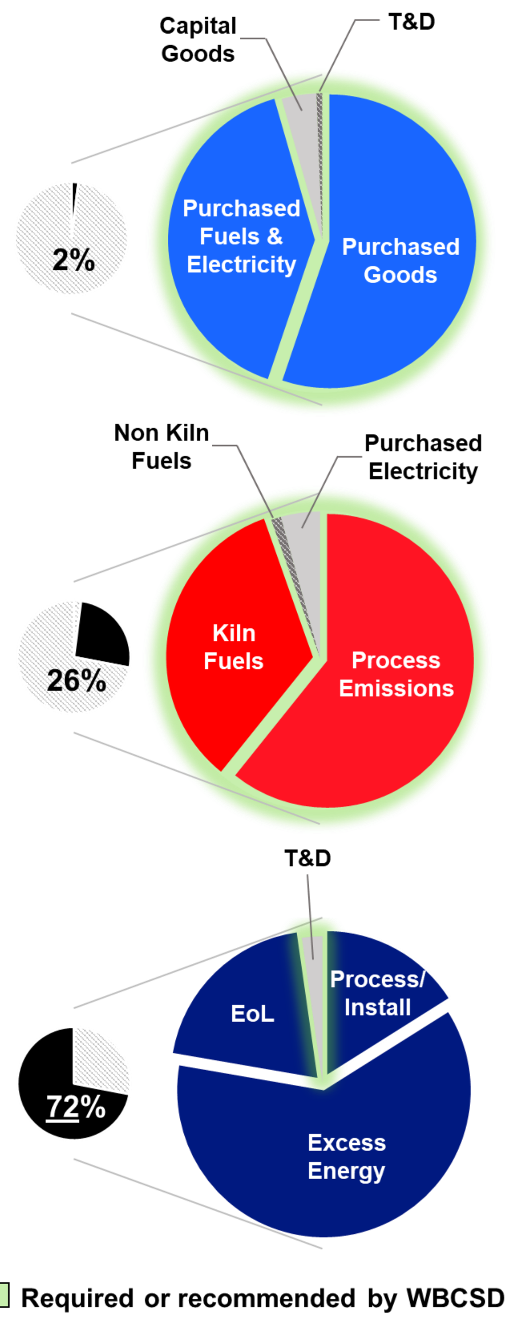

Figure 5.7-4. Breakdown of reportable emissions associated with cement-based products used in Florida homes built in 1940-2018; snapshot of 2018.

5.8 Discussion

Present protocols for GHG accounting of cement producers are limited to emissions which fall under the product stage in the building life cycle. However, the majority of building life cycle emissions derive from the construction, use, and end-of-life stages that occur much after the product stage. As buildings are one of the main end-use applications of CBPs, the construction, use, and end-of-life emissions of buildings are major contributors to reportable emissions within cement's value chain.

In this manuscript, we demonstrate that the contribution of latter-stage building life cycle emissions to cement's SEF is particularly prominent towards the end of the analysis period, as the existing housing stock grows over time, and a larger number of homes create operational energy usage emissions, or reach the end of their service life and create end-of-life emissions. To do this, we make use of LCIs and building LCA to aid current best practices for GHG accounting.

By considering a wider variety of building life cycle emissions, we expand required GHG accounting. While the GHGP guidelines, the general guidelines for GHG accounting, cover these emission categories, and the WBCSD guidelines, those specialized to cement producers, recognize them, these guidelines deem use and end-of-life emissions associated with end-use applications "too complex" to measure or model.

Figure 5.8-1 shows a complete list of scopes and categories captured in this study. We create a more complete picture of cement's SEF than current best practices. However, a truly complete picture needs to include a comprehensive range of residential and commercial buildings and infrastructure, as well as a comprehensive range of natural hazards.

Moreover, future studies can extend this work to explore scope 4 (or avoided) emissions. This scope captures environmental benefits, not just footprints. These benefits are characterized by comparing the current (baseline) scenario (in a world where CBPs are used in various applications) to an alternative scenario (in a world where all applications are replaced by competing construction materials). Scope 4 encompasses scope 1-3 as well as any other life cycle stage where differences arise. As scope 4 emissions are not actualized, they cannot be measured and need to be measured. Thus, the capability of LCA to model different scenarios is critical to rigorously investigate scope 4 emissions.

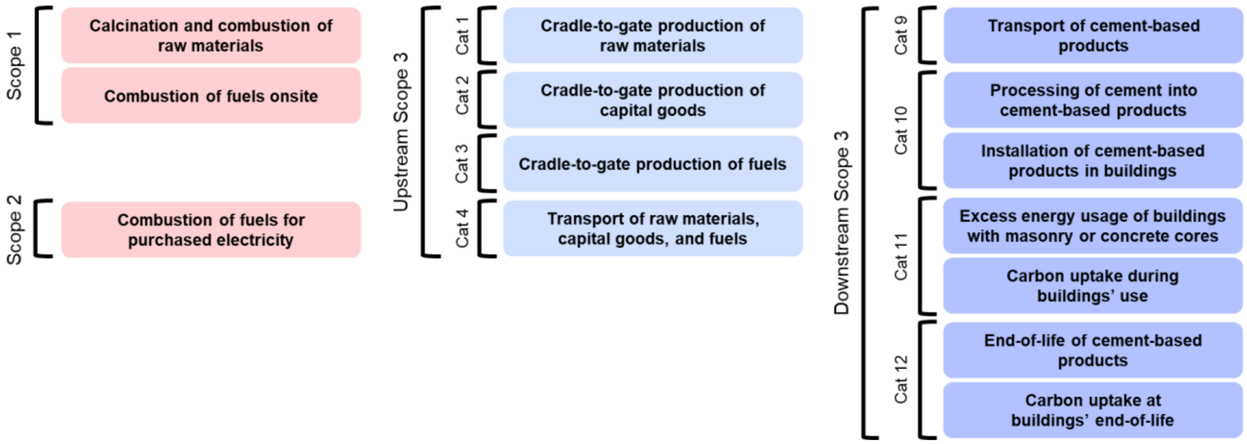

Figure 5.8-1. Emission scopes and categories within cement's value chain.

5.9 Data Availability Statement

All data, models, or code generated or used during the study are available for the corresponding author by request.

5.10 Acknowledgements

Research was carried out by the Concrete Sustainability Hub at MIT with funding provided by the Portland Cement Association (PCA) and the Ready Mixed Concrete (RMC) Research and Education Foundation.

5.11 Declaration of Interest Statement

The authors report there are no competing interests to declare.

5.12 References

References can be found at the end of this work.

6 Conclusion

The chapters of this work present the most comprehensive framework to date to assess the intersectional risks associated with design and policy decisions regarding the built environment. These risks involve the interplay of physical and economic stressors (**Chapter 2**), physical, economic, and social stressors (**Chapter 3**), and physical, economic, and environmental stressors (**Chapters 4 & 5**).

This work spans a variety of disciplines. **Chapters 2 & 3** pertain to loss estimation and regional planning for disaster risk reduction. **Chapter 4** pertains to building life cycle assessment (LCA) and measuring sustainability at a project level. **Chapter 5** pertains to greenhouse gas (GHG) accounting and measuring sustainability at industry or regional levels. **Chapters 4 & 5** also highlight that disaster risk reduction is a key part of reducing GHG emissions created by residential building construction.

In **Chapter 2**, neighborhood texture is defined to characterize the configuration of the surrounding neighborhood. Texture effects are incorporated into a widely-recognized loss estimation framework. This framework is applied to compute expected damages associated with each individual building in a community with hurricane wind exposure. The case study demonstrates that accounting for texture effects can as high as double expected damages. Overlooking these impacts leads to undervaluing hurricane wind mitigation.

In **Chapter 3**, the augmented loss estimation framework is combined with human behavior simulation. This combination is applied to compute expected damages associated with each resident household in each individual building. Resident households are attributed household annual income as well as demographic and socioeconomic characteristics. This allows to study the cost burden of expected damages across demographic and socioeconomic groups. The case study demonstrates that socially-vulnerable groups are disproportionately impacted by hurricane wind exposure, as they are likelier to be priced out of hazard repairs. If hurricane wind mitigation efforts are prioritized strategically, it is possible to prevent monetary damages on societal level and redistribute the cost burden of monetary damages on individual household level, doing so without significant trade-offs towards either of the respective performance metrics.

In **Chapter 4**, the augmented loss estimation framework is integrated into building LCA. This integration makes use of building archetype definition and loss functions from loss estimation as well as the capability to produce results with incomplete building information from streamlined building LCA. Incorporating hazard vulnerability into building LCA shifts the discussion of what construction materials constitute a 'green' building from solely focusing on initial construction emissions to considering the benefits of durability and hazard resilience which are reaped much later than initial construction stages. Accounting for hazard vulnerability can as high as double building embodied emissions. This more complete picture of building life cycle emissions helps map areas where repair and replacement emissions are the leading factor in determining the life cycle outcomes of construction material choice. The case study shows that the favorability of concrete is particularly pronounced in areas with high hurricane wind exposure and for large structures and/or structures lacking hurricane mitigation measures.

In **Chapter 5**, the integrated loss estimation and building LCA framework is extended to the GHG accounting of construction material sectors. Guidelines are developed for construction material sectors to model emission categories which are currently deemed too complex and difficult to measure. A precedent is formulated for industry, regional, or industry level policymaking to consider the construction, use, and end-of-life emissions of end-use applications associated with construction materials while strategizing GHG abatement. This directs GHG abatement efforts towards emission categories which are the largest contributors of SEFs, thus the most effective to tackle.

So far, the loss estimation component of this work has focused on hurricane wind loading. Future works can extend this approach to study other natural hazards, such as flooding, fires, or earthquakes. Such work could then be integrated with this work for an expansive, multi-hazard framework. As hazards like hurricanes, floods, and fires become more intense and/or frequent with the changing climate, the impacts of these hazards in terms of the dollar value or cost burden of monetary damages or GHG emissions will only go up if no action is taken. The design of the housing stock is crucial for both climate mitigation (reducing GHG emissions released into the atmosphere to slow down climate change) and climate adaptation (which includes strengthening structures to withstand climate events).

While the loss estimation component of this work includes a wider range of residential construction types, the building LCA component has focused on single-family dwellings. Future works can develop methods for streamlined building LCA for other residential and commercial construction types. Such work could start with generalized models for low-, mid-, and high-rise geometries, and then specialize these models for live and dead loads representing different residential and commercial end-use applications. This is particularly important for industry or regional efforts for GHG abatement. While single-family dwellings comprise a large number of structures in the U.S., a high-rise structure consumes multiples of the amounts of materials used in a single-family dwelling. Thus, triaging across construction types relies on a thorough investigation of each.

There remain gaps in defining building archetypes, characterizing loss functions, defining cost and emission models, and incorporating climate change into hurricane wind loading scenarios.

Building archetypes, and their associated loss functions and cost and emission models, currently do not account for regional and timestamp differences in code adoption and enforcement, availability of grant and insurance benefits programs, and technological advances in construction methods and materials, all of which impact the performance of the housing stock. Additionally, the hurricane wind loading scenarios presented in **Chapters 4 & 5** represent percentiles in present wind speed distributions, which derive from historical hurricane events. Climate change will likely shift the higher percentile scenarios to lower percentiles, as high-category hurricanes become more frequent.

Further directions for future work can be found in the respective **Discussion** sections of each chapter. This work, as it stands, encompasses the best of the author's knowledge on data and modeling available at the date of submission. Although this work has gone through the diligent review of the author's thesis committee, several of the chapters are still under peer review for publication. If available, please refer to the published materials for the most up-to-date version of this work, as additions may have been made to the content or geographical scope presented here.

7 Chapter 2 Supplementary Materials

7.1 Aid to Literature Review

Table 7.1-1. Aid to literature review.

	Terrain	Texture
Main Message	In denser (rougher) areas, lower wind loads, lower expected losses.	In dense areas with less disorder (though perfect order not realistic), higher maximum wind loads.
Theoretical Backing	Upwind terrain effects – Rougher areas create friction and turbulence which affect the mean wind speed and wind speed gradient in the Internal Sublayer (ISL) (Davenport, 1960).	Urban canyon effects – Less disorder creates channels (or canyons) through which turbulence is amplified.
Flow Type	Depending on planar density; Smooth, semi-smooth, wake-interference (if considerably inhomogeneous), or skimming flow (Wieringa, 1993).	Mostly wake-interference flow (fewer meshing points for “smoother” flows).
Flow Boundary Layer	ISL (above “blending height” where no more recirculation eddies and horizontal homogeneity can be assumed) (Wieringa, 1993).	Transition Sublayer (TSL) (where there are recirculation eddies).
Applicational Input	Visual site survey (descriptions, photographs, or LULC maps) (though wind tunnel tests recommended for high-rise cities) (Davenport, 1960).	Building footprints (required to extract latitudes, longitudes, and footprint areas).
Application	Surface roughness length lists (matching descriptions to ranges or characteristic values for roughness length) (typically for homogeneous stretches) (Wieringa, 1992, 1993).	Regression model (using latitudes, longitudes, and footprint areas).
Observations	Station records – To quantify upwind terrain effects (Wieringa, 1992, 1993). Wind tunnel tests – To characterize roughness elements (Seginer, 1974).	CFD simulations – To quantify urban canyon effects (160 simulations in total). RDF – To quantify (and replicate) disorder.
Observed Areas	Actual towns and cities (station records) (Karlsson, 1986; Shiotani, 1962; Steyn, 1982; Yersel & Goble, 1986). Objects (such as bushel baskets) with regular size, height, and spacing (wind tunnel tests) (Lettau, 1969).	Sample cities with: Replicated texture (through Reverse MC on RDF), random footprint areas (sampled from local distribution), and constant roof height (9.5 m) (CFD).
Observed What?	Mean wind speed (wind profile), or mean frictional velocity (station records). Obstruction height, obstruction side-area, and surface area (wind tunnel tests).	Pressure and velocities (at simulated convergence) (read from meshing points) (CFD).
Observed Where?	Towers – 20-100 m high, several km in fetch (terrain described qualitatively) (station records). Turntables (wind tunnel tests).	Meshing points on building facades (sample size of 100-300 buildings) (CFD). Reference buildings – 3.5 times density length in radius (RFD).

Table 7.1-1 (continued). Aid to literature review.

Measurements	At least 2 different heights on a single tower, 10s to 100s over months or years (station records). Several repetitions (wind tunnel tests).	40 sample cities under Saffir-Simpson Category 5 hurricanes simulated in four directions (CFD). Finer mesh for: More turbulent flows and more complexity (trade-off between complexity and accuracy).
Modeled Quantities	Surface roughness lengths, drag coefficients, or exponents of power law profiles (latter two height-dependent) (Wieringa, 1992).	Drag coefficients (from differences of pressures averaged across meshing points on front and back facades).

7.2 Regional Assumptions for Prevalence of Mitigation

Table 7.2-1. Prevalence of mitigation in Southeast Florida; % of buildings (FEMA 2019).

	MM1	MM2	MM3	MM4	MM5	MM6	Avg
RES1	29	84	71	0	0	0	46
RES2	0	0	0	0	0	71	35
RES3A	0	81	70	0	0	0	30
RES3B	0	81	70	0	0	0	30
RES3C	0	53	47	0	0	0	20
RES3D	0	53	47	0	0	0	20
RES3E	0	53	47	0	0	0	20
RES3F	0	53	47	0	0	0	20

Note: mitigation measures for RES1 are MM1, MM2, MM3 and MM5; that for RES2 are MM1 and MM6; and, that for RES3 are MM1, MM2, MM3, MM4 and MM5.

Table 7.2-2. Prevalence of mitigation in South Florida; % of buildings (FEMA 2019).

	MM1	MM2	MM3	MM4	MM5	MM6	Avg
RES1	14	84	51	0	0	0	37
RES2	0	0	0	0	0	74	37
RES3A	0	81	50	0	0	0	26
RES3B	0	81	50	0	0	0	26
RES3C	0	53	33	0	0	0	17
RES3D	0	53	33	0	0	0	17
RES3E	0	53	33	0	0	0	17
RES3F	0	53	33	0	0	0	17

Note: same as **Table 7.2-1**.

Table 7.2-3. Prevalence of mitigation in Central Florida; % of buildings (FEMA 2019).

	MM1	MM2	MM3	MM4	MM5	MM6	Avg
RES1	5	72	67	0	0	0	36
RES2	0	0	0	0	0	73	36
RES3A	0	69	66	0	0	0	27
RES3B	0	69	66	0	0	0	27
RES3C	0	45	44	0	0	0	18
RES3D	0	45	44	0	0	0	18
RES3E	0	45	44	0	0	0	18
RES3F	0	45	44	0	0	0	18

Note: same as **Table 7.2-1**.

Table 7.2-4. Prevalence of mitigation in North Florida; % of buildings (FEMA 2019).

	MM1	MM2	MM3	MM4	MM5	MM6	Avg
RES1	8	78	57	0	0	0	36
RES2	0	0	0	0	0	74	37
RES3A	0	76	56	0	0	0	26
RES3B	0	76	56	0	0	0	26
RES3C	0	50	37	0	0	0	17
RES3D	0	50	37	0	0	0	17
RES3E	0	50	37	0	0	0	17
RES3F	0	50	37	0	0	0	17

Note: same as **Table 7.2-1**.

7.3 Additional Tables

Table 7.3-1. List of building types considered.

Code	Description
WSF1	Wood single-family dwellings, single story
WSF2	Wood single-family dwellings, 2+ stories
WMUH1	Wood multi-unit housing, single story
WMUH2	Wood multi-unit housing, 2 stories
WMUH3	Wood multi-unit housing, 3+ stories
MSF1	Masonry single-family dwellings, single story
MSF2	Masonry single-family dwellings, 2+ stories
MMUH1	Masonry multi-unit housing, single story
MMUH2	Masonry multi-unit housing, 2 stories
MMUH3	Masonry multi-unit housing, 3+ stories
MERBL	Masonry engineered residential buildings, low-rise
MERBM	Masonry engineered residential buildings, mid-rise
MERBH	Masonry engineered residential buildings, high-rise
CERBL	Concrete engineered residential buildings, low-rise
CERBM	Concrete engineered residential buildings, mid-rise
CERBH	Concrete engineered residential buildings, high-rise
SPMBS	Steel pre-engineered buildings, small
SPMBM	Steel pre-engineered buildings, medium
SPMBL	Steel pre-engineered buildings, large
SERBL	Steel engineered residential buildings, low-rise
SERBM	Steel engineered residential buildings, mid-rise
SERBH	Steel engineered residential buildings, high-rise
MHPHUD	Manufactured homes, pre-HUD
MH76HUD	Manufactured homes, post-1976 HUD
MH94HUDI	Manufactured homes, post-1994 HUD Wind Zone I
MH94HUDII	Manufactured homes, post-1994 HUD Wind Zone II
MH94HUDIII	Manufactured homes, post-1994 HUD Wind Zone III

Note: Nomenclature for codes borrowed from HAZUS.

7.4 Additional Figures

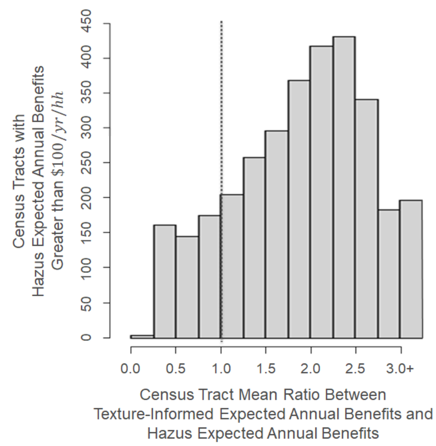

Figure 7.4-1. Histogram of Census Tract mean ratio between texture-informed expected annual benefits and HAZUS expected annual benefits; A majority of Census Tracts exhibit an increase in expected annual benefits of mitigating homes.

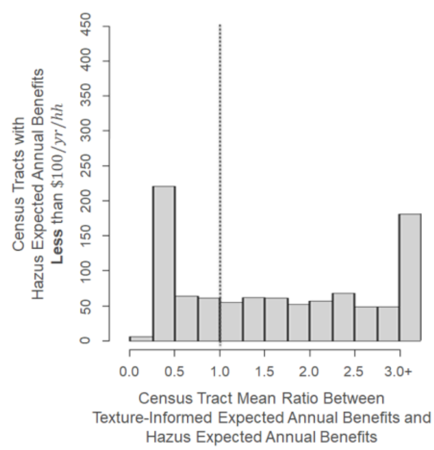

Figure 7.4-2. Histogram of Census Tract mean ratio between texture-informed expected annual benefits and HAZUS expected annual benefits; A majority of Census Tracts exhibit an increase in expected annual benefits of mitigating homes.

8 Chapter 3 Supplementary Materials

8.1 Analyses of States

Results for State of Florida

For the State of Florida, we simulated 7,570,518 households, making use of data and shapefiles from 67 counties, 4,131 Census Tracts, 14,885 Census Block Groups, and more than 3,000,000 building footprints (**Table 8.1-1**).

In 67 / 67 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $1,133 / year / household (or 1% of replacement cost, or 2% of annual income). This is as high as $7,661 / year / household (or 18% of replacement cost, or 29% of annual income) across mobile homes, and as low as $561 / year / household (or .5% of replacement cost, or 2% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-2**).

We found that 483,127 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-3**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with disability, that are single-parent households, that speak English less than "well", and/or that live in mobile homes (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 637,754 / year if no mitigation measures were applied, and 301,135 / year if all of the mitigation measures were applied (**Table 8.1-4**). So, 336,619 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 54% of this avoidable price-out currently remains in the state.

The value of monetary damage would be \$16.90 billion / year if no mitigation measures were applied, and \$8.20 billion / year if all of the mitigation measures were applied (**Table 8.1-5**). So, \$8.70 billion / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 51% of this avoidable monetary damage currently remains in the state.

Table 8.1-1. Percent prevalence of each group; households (Florida).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	7,570,518	4,982,055	417,042	769,573	1,401,848
Median income ($/yr)	62,500	87,500	20,000	20,000	42,500
Below poverty (%)	20	15	32	35	26
Unemployed (%)	6	6	8	8	7
No high school diploma (%)	11	10	13	13	12
Aged 65yo or older (%)	21	20	25	24	23
Aged 17yo or younger (%)	19	19	19	20	19
With disability (%)	14	13	18	18	15
Single-parent household (%)	8	7	10	10	8
Minority (%)	40	39	46	45	41
English less than “well” (%)	6	5	7	7	6
Multi-unit structures (%)	19	-	-	-	100
Mobile homes (%)	6	-	100	-	-
Crowding (%)	3	3	3	3	3
No vehicles (%)	8	9	5	5	7

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-2. Expected annual loss (EAL) metrics; median (Florida).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	1,133	1	2
RES1	1,138	1	2
RES2	7,661	18	29
RES3A-C	561	.5	2
RES3D-F	1,043	1	2
Below poverty	952	1	10
Unemployed	1,011	1	4
No high school diploma	1,099	1	3
Aged 65yo or older	1,173	1	2
Aged 17yo or younger	1,091	1	2
With disability	999	1	3
Single-parent household	1,078	1	3
Minority	1,391	1	3
English less than "well"	1,719	1	5
Multi-unit structures	1,043	1	2
Mobile homes	7,661	18	29
Crowding	1,330	1	3
No vehicles	1,141	1	1

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-3. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Florida).

Description	Population	Cost-Burdened	Ratio
Total (#)	7,570,518	483,127	-
Median income ($/yr)	62,500	5,000	-
Below poverty (%)	20	68	**3.40**
Unemployed (%)	6	12	**2.00**
No high school diploma (%)	11	15	**1.36**
Aged 65yo or older (%)	21	26	**1.24**
Aged 17yo or younger (%)	19	20	**1.05**
With disability (%)	14	21	**1.50**
Single-parent household (%)	8	12	**1.50**
Minority (%)	40	54	**1.35**
English less than “well” (%)	6	12	**2.00**
Multi-unit structures (%)	19	13	**.68**
Mobile homes (%)	6	31	**5.17**
Crowding (%)	3	3	**1.00**
No vehicles (%)	8	1	**.13**

Table 8.1-4. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Florida).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	301,135	483,127	637,754
HAZUS	171,786	251,032	322,743

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-5. Total expected monetary damage by mitigation level; $ billion / year (Florida).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	8.20	12.68	16.90
HAZUS	4.54	7.01	9.07

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Results for State of Georgia

For the State of Georgia, we simulated 3,704,120 households, making use of data and shapefiles from 159 counties, 1,953 Census Tracts, 6,359 Census Block Groups, and more than 2,000,000 building footprints (**Table 8.1-6**).

In 39 / 159 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $66 / year / household (or .04% of replacement cost, or .1% of annual income). This is as high as $2,203 / year / household (or 5% of replacement cost, or 8% of annual income) across mobile homes, and as low as $19 / year / household (or .01% of replacement cost, or .1% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-7**).

We found that 9,511 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-8**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with no high school diploma, that have members with disability, that are single-parent households, that live in mobile homes, and/or that experience crowding (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 10,662 / year if no mitigation measures were applied, and 7,357 / year if all of the mitigation measures were applied (**Table 8.1-9**). So, 3,305 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 65% of this avoidable price-out currently remains in the state.

The value of monetary damage would be $377 million / year if no mitigation measures were applied, and $262 million / year if all of the mitigation measures were applied (**Table 8.1-10**). So, $115 million / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 70% of this avoidable monetary damage currently remains in the state.

Table 8.1-6. Percent prevalence of each group; households (Georgia).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	3,704,120	2,453,240	205,053	380,144	665,683
Median income ($/yr)	62,500	87,500	20,000	20,000	30,000
Below poverty (%)	21	16	35	37	29
Unemployed (%)	6	6	8	8	7
No high school diploma (%)	13	12	15	15	14
Aged 65yo or older (%)	14	13	16	16	14
Aged 17yo or younger (%)	24	23	25	25	24
With disability (%)	12	11	16	16	14
Single-parent household (%)	10	9	13	13	11
Minority (%)	45	43	51	51	46
English less than “well” (%)	3	2	3	3	3
Multi-unit structures (%)	18	-	-	-	100
Mobile homes (%)	6	-	100	-	-
Crowding (%)	2	2	2	2	2
No vehicles (%)	8	10	5	5	7

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-7. Expected annual loss (EAL) metrics; median (Georgia).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	66	.04	.1
RES1	65	.04	.1
RES2	2,203	5	8
RES3A-C	19	.01	.1
RES3D-F	58	.04	.1
Below poverty	61	.04	1
Unemployed	63	.04	.2
No high school diploma	60	.04	.2
Aged 65yo or older	67	.04	.2
Aged 17yo or younger	64	.04	.1
With disability	63	.04	.2
Single-parent household	63	.04	.2
Minority	61	.04	.2
English less than "well"	71	.04	.2
Multi-unit structures	58	.04	.1
Mobile homes	2,203	5	8
Crowding	62	.04	.1
No vehicles	61	.04	.1

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-8. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Georgia).

Description	Population	Cost-Burdened	Ratio
Total (#)	3,704,120	9,511	-
Median income ($/yr)	62,500	5,000	-
Below poverty (%)	21	91	**4.33**
Unemployed (%)	6	15	**2.50**
No high school diploma (%)	13	20	**1.54**
Aged 65yo or older (%)	14	15	**1.07**
Aged 17yo or younger (%)	24	28	**1.17**
With disability (%)	12	23	**1.92**
Single-parent household (%)	10	20	**2.00**
Minority (%)	45	58	**1.29**
English less than “well” (%)	3	2	**.67**
Multi-unit structures (%)	18	.1	**.01**
Mobile homes (%)	6	94	**15.67**
Crowding (%)	2	3	**1.50**
No vehicles (%)	8	1	**.13**

Table 8.1-9. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Georgia).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	7,357	9,511	10,662
HAZUS	6,950	8,658	9,238

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-10. Total expected monetary damage by mitigation level; $ million / year (Georgia).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	262	343	377
HAZUS	248	314	336

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Results for State of Alabama

For the State of Alabama, we simulated 1,856,554 households, making use of data and shapefiles from 67 counties, 1,173 Census Tracts, 4,022 Census Block Groups, and more than 1,000,000 building footprints (**Table 8.1-11**).

In 44 / 67 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $50 / year / household (or .03% of replacement cost, or .1% of annual income). This is as high as $1,912 / year / household (or 5% of replacement cost, or 7% of annual income) across mobile homes, and as low as $11 / year / household (or .01% of replacement cost, or .1% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-12**).

We found that 29,708 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-13**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with disability, that are single-parent households, that belong to minority, and/or that live in mobile homes (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 33,405 / year if no mitigation measures were applied, and 22,233 / year if all of the mitigation measures were applied (**Table 8.1-14**). So, 11,172 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 67% of this avoidable price-out currently remains in the state.

The value of monetary damage would be $859 million / year if no mitigation measures were applied, and $563 million / year if all of the mitigation measures were applied (**Table 8.1-15**). So, $296 million / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 67% of this avoidable monetary damage currently remains in the state.

Table 8.1-11. Percent prevalence of each group; households (Alabama).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	1,856,554	1,355,968	149,869	224,661	126,056
Median income ($/yr)	62,500	62,500	30,000	20,000	20,000
Below poverty (%)	21	14	32	43	37
Unemployed (%)	6	5	8	9	8
No high school diploma (%)	13	12	16	17	16
Aged 65yo or older (%)	16	15	19	18	18
Aged 17yo or younger (%)	22	22	22	23	22
With disability (%)	16	14	20	21	20
Single-parent household (%)	8	7	11	12	11
Minority (%)	32	30	39	40	36
English less than “well” (%)	1	1	1	1	1
Multi-unit structures (%)	7	-	-	-	100
Mobile homes (%)	8	-	100	-	-
Crowding (%)	0	0	0	0	0
No vehicles (%)	8	9	5	4	5

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-12. Expected annual loss (EAL) metrics; median (Alabama).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	50	.03	.1
RES1	46	.03	.1
RES2	1,912	5	7
RES3A-C	11	.01	.1
RES3D-F	27	.02	.1
Below poverty	50	.03	.5
Unemployed	50	.03	.2
No high school diploma	49	.03	.1
Aged 65yo or older	54	.03	.1
Aged 17yo or younger	50	.03	.1
With disability	47	.03	.1
Single-parent household	53	.03	.2
Minority	56	.03	.2
English less than "well"	48	.03	.1
Multi-unit structures	27	.02	.1
Mobile homes	1,912	5	7
Crowding	-	-	-
No vehicles	58	.03	.1

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-13. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Alabama).

Description	Population	Cost-Burdened	Ratio
Total (#)	1,856,554	29,708	-
Median income ($/yr)	62,500	12,500	-
Below poverty (%)	21	74	**3.52**
Unemployed (%)	6	13	**2.17**
No high school diploma (%)	13	18	**1.38**
Aged 65yo or older (%)	16	19	**1.19**
Aged 17yo or younger (%)	22	25	**1.14**
With disability (%)	16	24	**1.50**
Single-parent household (%)	8	15	**1.88**
Minority (%)	32	49	**1.53**
English less than “well” (%)	1	1	**1.00**
Multi-unit structures (%)	7	2	**.29**
Mobile homes (%)	8	63	**7.88**
Crowding (%)	0	0	**-**
No vehicles (%)	8	1	**.13**

Table 8.1-14. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Alabama).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	22,233	29,708	33,405
HAZUS	18,230	24,485	26,634

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-15. Total expected monetary damage by mitigation level; $ million / year (Alabama).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	563	762	859
HAZUS	461	607	654

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Results for State of Mississippi

For the State of Mississippi, we simulated 1,101,348 households, making use of data and shapefiles from 82 counties, 654 Census Tracts, 2,289 Census Block Groups, and more than 600,000 building footprints (**Table 8.1-16**).

In 36 / 82 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $84 / year / household (or .1% of replacement cost, or .2% of annual income). This is as high as $2,522 / year / household (or 6% of replacement cost, or 9% of annual income) across mobile homes, and as low as $17 / year / household (or .02% of replacement cost, or .1% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-17**).

We found that 16,343 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-18**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with disability, that are single-parent households, and/or that live in mobile homes (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 18,383 / year if no mitigation measures were applied, and 12,445 / year if all of the mitigation measures were applied (**Table 8.1-19**). So, 5,938 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 66% of this avoidable price-out currently remains in the state.

The value of monetary damage would be $461 million / year if no mitigation measures were applied, and $311 million / year if all of the mitigation measures were applied (**Table 8.1-20**).

So, $150 million / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 66% of this avoidable monetary damage currently remains in the state.

Table 8.1-16. Percent prevalence of each group; households (Mississippi).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	1,101,348	800,279	88,826	132,576	79,667
Median income ($/yr)	62,500	62,500	30,000	20,000	30,000
Below poverty (%)	21	15	33	45	36
Unemployed (%)	7	7	9	11	9
No high school diploma (%)	15	14	18	19	17
Aged 65yo or older (%)	15	14	18	17	17
Aged 17yo or younger (%)	23	23	24	25	24
With disability (%)	15	14	20	21	18
Single-parent household (%)	10	8	13	14	12
Minority (%)	39	36	47	49	44
English less than “well” (%)	1	1	1	1	1
Multi-unit structures (%)	7	-	-	-	100
Mobile homes (%)	8	-	100	-	-
Crowding (%)	0	0	0	0	0
No vehicles (%)	9	11	6	5	6

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-17. Expected annual loss (EAL) metrics; median (Mississippi).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	84	.1	.2
RES1	76	.05	.1
RES2	2,522	6	9
RES3A-C	17	.02	.1
RES3D-F	32	.02	.1
Below poverty	84	.1	1
Unemployed	99	.1	.4
No high school diploma	88	.1	.3
Aged 65yo or older	91	.1	.2
Aged 17yo or younger	83	.1	.2
With disability	110	.1	.4
Single-parent household	87	.1	.4
Minority	57	.03	.2
English less than “well”	117	.1	.3
Multi-unit structures	32	.02	.1
Mobile homes	2,522	6	9
Crowding	-	-	-
No vehicles	71	.05	.1

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-18. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Mississippi).

Description	Population	Cost-Burdened	Ratio
Total (#)	1,101,348	16,343	-
Median income ($/yr)	62,500	5,000	-
Below poverty (%)	21	78	**3.71**
Unemployed (%)	7	15	**2.14**
No high school diploma (%)	15	20	**1.33**
Aged 65yo or older (%)	15	18	**1.20**
Aged 17yo or younger (%)	23	27	**1.17**
With disability (%)	15	26	**1.73**
Single-parent household (%)	10	18	**1.80**
Minority (%)	39	51	**1.31**
English less than "well" (%)	1	1	**1.00**
Multi-unit structures (%)	7	1	**.14**
Mobile homes (%)	8	70	**8.75**
Crowding (%)	0	0	**-**
No vehicles (%)	9	1	**.11**

Table 8.1-19. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Mississippi).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	12,445	16,343	18,383
HAZUS	11,127	14,614	15,992

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-20. Total expected monetary damage by mitigation level; $ million / year (Mississippi).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	311	410	461
HAZUS	277	368	399

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Results for State of Louisiana

For the State of Louisiana, we simulated 1,724,092 households, making use of data and shapefiles from 64 counties, 1,125 Census Tracts, 3,688 Census Block Groups, and more than 1,000,000 building footprints (**Table 8.1-21**).

In 41 / 64 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $537 / year / household (or .3% of replacement cost, or 1% of annual income). This is as high as $5,476 / year / household (or 13% of replacement cost, or 17% of annual income) across mobile homes, and as low as $186 / year / household (or .2% of replacement cost, or 1% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-22**).

We found that 55,669 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-23**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with no high school diploma, that have members with disability, that are single-parent households, that belong to minority, that speak English less than “well”, and/or that live in mobile homes (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 65,177 / year if no mitigation measures were applied, and 40,197 / year if all of the mitigation measures were applied (**Table 8.1-24**). So, 24,980 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 62% of this avoidable price-out currently remains in the state.

The value of monetary damage would be $1,759 million / year if no mitigation measures were applied, and $1,080 million / year if all of the mitigation measures were applied (**Table 8.1-25**). So, $679 million / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 64% of this avoidable monetary damage currently remains in the state.

Table 8.1-21. Percent prevalence of each group; households (Louisiana).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	1,724,092	1,162,367	96,663	201,534	263,528
Median income ($/yr)	62,500	87,500	30,000	20,000	42,500
Below poverty (%)	21	16	30	42	27
Unemployed (%)	6	6	8	9	7
No high school diploma (%)	14	13	16	18	15
Aged 65yo or older (%)	14	13	16	17	16
Aged 17yo or younger (%)	23	23	24	25	24
With disability (%)	14	13	18	19	16
Single-parent household (%)	10	9	12	14	11
Minority (%)	38	35	44	48	41
English less than “well” (%)	1	1	2	2	1
Multi-unit structures (%)	15	-	-	-	100
Mobile homes (%)	6	-	100	-	-
Crowding (%)	2	2	2	2	2
No vehicles (%)	11	13	8	6	9

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-22. Expected annual loss (EAL) metrics; median (Louisiana).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	537	.3	1
RES1	536	.3	1
RES2	5,476	13	17
RES3A-C	186	.2	1
RES3D-F	408	.3	1
Below poverty	477	.3	5
Unemployed	502	.3	2
No high school diploma	494	.3	1
Aged 65yo or older	536	.3	1
Aged 17yo or younger	485	.3	1
With disability	481	.3	2
Single-parent household	505	.3	2
Minority	688	.4	2
English less than "well"	956	1	2
Multi-unit structures	408	.3	1
Mobile homes	5,476	13	17
Crowding	462	.3	1
No vehicles	736	.4	1

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-23. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Louisiana).

Description	Population	Cost-Burdened	Ratio
Total (#)	1,724,092	55,669	-
Median income ($/yr)	62,500	5,000	-
Below poverty (%)	21	78	**3.71**
Unemployed (%)	6	13	**2.17**
No high school diploma (%)	14	21	**1.50**
Aged 65yo or older (%)	14	17	**1.21**
Aged 17yo or younger (%)	23	26	**1.13**
With disability (%)	14	23	**1.65**
Single-parent household (%)	10	17	**1.70**
Minority (%)	38	59	**1.55**
English less than “well” (%)	1	3	**3.00**
Multi-unit structures (%)	15	4	**.27**
Mobile homes (%)	6	44	**7.33**
Crowding (%)	2	2	**1.00**
No vehicles (%)	11	2	**.18**

Table 8.1-24. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Louisiana).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	40,197	55,669	65,177
HAZUS	23,896	28,617	31,425

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-25. Total expected monetary damage by mitigation level; $ million / year (Louisiana).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	1,080	1,517	1,759
HAZUS	665	882	984

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Results for State of Texas

For the State of Texas, we simulated 9,373,319 households, making use of data and shapefiles from 254 counties, 5,214 Census Tracts, 17,319 Census Block Groups, and more than 5,000,000 building footprints (**Table 8.1-26**).

In 164 / 254 counties, at least 10% of households are exposed to hurricane-related losses greater than $100 / year. Across these counties, median expected annual losses (EALs) are $149 / year / household (or .1% of replacement cost, or .3% of annual income). This is as high as $1,862 / year / household (or 4% of replacement cost, or 4% of annual income) across mobile homes, and as low as $70 / year / household (or .1% of replacement cost, or .4% of annual income) across low- to mid-rise multi-unit housing (**Table 8.1-27**).

We found that 117,591 households are likely to face financially challenging levels of hurricane losses and repair needs (**Table 8.1-28**). Socially vulnerable groups are overrepresented among these households. This overrepresentation is highest for households that are below the poverty line, that have members who are unemployed, that have members with no high school diploma, that have members with disability, that are single-parent households, that speak English less than "well", and/or that live in mobile homes (ratios greater than or equal to 1.5).

The number of households severely cost-burdened by hurricane repairs would be 143,343 / year if no mitigation measures were applied, and 81,875 / year if all of the mitigation measures were applied (**Table 8.1-29**). So, 61,468 households / year could be removed from price-out by using these mitigation measures. Our model results indicate that 58% of this avoidable price-out currently remains in the state.

The value of monetary damage would be $4,603 million / year if no mitigation measures were applied, and $2,826 million / year if all of the mitigation measures were applied (**Table 8.1-30**). So, $1,777 million / year of potential monetary damage could be prevented by using mitigation measures. Our model results indicate that 62% of this avoidable monetary damage currently remains in the state.

Table 8.1-26. Percent prevalence of each group; households (Texas).

Description/Code	Population	RES1	RES2	RES3A-C	RES3D-F
Total (#)	9,373,319	6,284,120	525,121	1,085,636	1,478,442
Median income ($/yr)	62,500	87,500	30,000	20,000	42,500
Below poverty (%)	22	16	30	42	27
Unemployed (%)	5	5	6	7	6
No high school diploma (%)	16	15	18	19	16
Aged 65yo or older (%)	13	12	14	15	14
Aged 17yo or younger (%)	25	25	26	27	25
With disability (%)	12	11	14	16	13
Single-parent household (%)	10	9	12	14	11
Minority (%)	54	52	60	62	54
English less than "well" (%)	6	6	8	9	7
Multi-unit structures (%)	16	-	-	-	100
Mobile homes (%)	6	-	100	-	-
Crowding (%)	4	4	5	5	4
No vehicles (%)	6	7	5	3	5

Note: RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-27. Expected annual loss (EAL) metrics; median (Texas).

Description/Code	AD ($/yr)	PRC (%/yr)	PAI (%/yr)
Population	149	.1	.3
RES1	158	.1	.3
RES2	1,862	4	4
RES3A-C	70	.1	.4
RES3D-F	91	.1	.3
Below poverty	136	.1	2
Unemployed	152	.1	1
No high school diploma	152	.1	1
Aged 65yo or older	144	.1	.4
Aged 17yo or younger	152	.1	.4
With disability	140	.1	1
Single-parent household	148	.1	1
Minority	161	.1	.5
English less than "well"	169	.1	1
Multi-unit structures	91	.1	.3
Mobile homes	1,862	4	4
Crowding	154	.1	.4
No vehicles	152	.1	.2

Note: medians limited to households in counties with at least 10% of population exposed to hurricane-related losses greater than $100 / year; AD = absolute-dollar EALs, PRC = per-replacement-cost EALs, PAI = per-annual-income EALs; RES1 = single-family dwellings, RES2 = mobile homes, RES3A-C = low- to mid-rise multi-unit housing, RES3D-F = mid- to high-rise multi-unit housing.

Table 8.1-28. Percent prevalence of each group among severely cost-burdened households (i.e., expecting hurricane repairs which exceed 1/4 of household annual income); households (Texas).

Description	Population	Cost-Burdened	Ratio
Total (#)	9,373,319	117,591	-
Median income ($/yr)	62,500	5,000	-
Below poverty (%)	22	85	**3.86**
Unemployed (%)	5	12	**2.40**
No high school diploma (%)	16	24	**1.50**
Aged 65yo or older (%)	13	14	**1.08**
Aged 17yo or younger (%)	25	29	**1.16**
With disability (%)	12	19	**1.58**
Single-parent household (%)	10	18	**1.80**
Minority (%)	54	74	**1.37**
English less than “well” (%)	6	12	**2.00**
Multi-unit structures (%)	16	4	**.25**
Mobile homes (%)	6	41	**6.83**
Crowding (%)	4	5	**1.25**
No vehicles (%)	6	1	**.17**

Table 8.1-29. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year (Texas).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	81,875	117,591	143,343
HAZUS	18,002	21,824	23,543

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.1-30. Total expected monetary damage by mitigation level; $ million / year (Texas).

	Fully Mitigated	Current Estimate	Fully Unmitigated
EAL	2,826	3,927	4,603
HAZUS	773	1,065	1,171

Note: EAL = expected annual loss metric, HAZUS = conventional EAL estimate not accounting for texture effects.

8.2 Additional Tables

Table 8.2-1. Correlation of expected annual loss (EAL) metrics; Spearman correlation coefficient.

	AD	PRC	PAI
HAZUS	.65	.36	.83

Note: AD = absolute-dollar EALs ($ / year / household), PRC = per-replacement-cost EALs (% / year / household), PAI = per-annual-income EALs (% / year / household); HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.2-2. Expected number of households severely cost-burdened by monetary damage by mitigation level; households / year.

	Fully Mitigated	Current Estimate	Fully Unmitigated
HAZUS	12,902	21,653	31,309

Note: HAZUS = conventional EAL estimate not accounting for texture effects.

Table 8.2-3. Total expected monetary damage by mitigation level; $ billion / year.

	Fully Mitigated	Current Estimate	Fully Unmitigated
HAZUS	.44	.69	.97

Note: HAZUS = conventional EAL estimate not accounting for texture effects.

8.3 Additional Figures

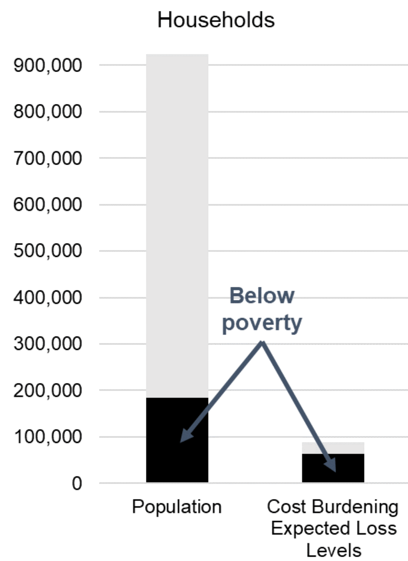

Figure 8.3-1. Number of households severely cost-burdened by hurricane repairs and portion below the poverty line (dark gray bars).

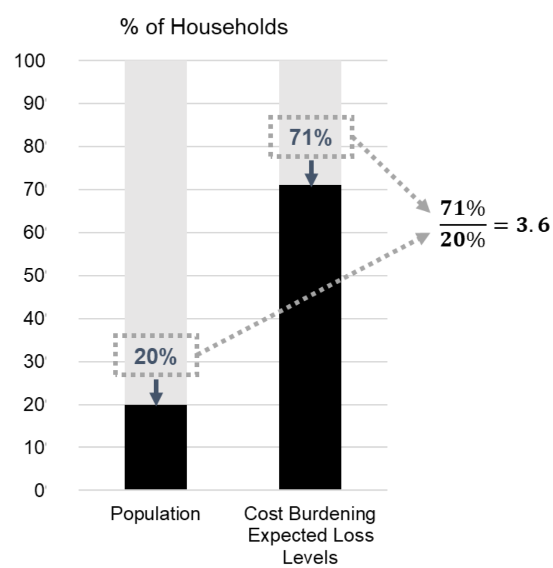

Figure 8.3-2. Percent of households severely cost-burdened by hurricane repairs and portion below the poverty line (dark gray bars).

9 Chapter 4 Supplementary Materials

9.1 Additional Tables

Table 9.1-1. Relationship between building stage emissions for concrete archetypes and continuous inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
ls	.62	.19	.93	-.02	-.02	.68	.51	.00	-.01
LivingArea	.28	.02	.23	.78	.86	.44	.32	.28	.35
Bedrooms	.05	.01	.16	-.02	-.02	.00	-.02	-.02	-.02
Stories	.20	.38	.08	.18	.05	.30	.05	-.06	-.09
AspectRatio	.06	.13	.02	.03	.06	-.02	.01	.01	.02
DegreeFromS	.00	-.02	-.01	-.01	-.01	.00	.00	-.01	.00
RoofPitch	.02	.02	.00	.08	.07	.04	.05	.06	.04
FrontWWR	.06	.13	.01	-.01	-.02	.05	.02	.10	.09
BackWWR	.04	.16	-.01	.00	-.02	.06	.03	.11	.10
SideWWR	.04	.03	.01	.00	-.02	.06	.04	-.02	-.02
SlabU	.00	.21	-.04	-.27	-.35	-.03	-.12	-.14	-.19
RoofU	.03	.00	.00	-.03	.01	.00	.01	-.12	-.04
WinU	.07	.05	-.02	-.02	.10	.02	.23	-.02	.10
WinSHGC	.11	.05	-.02	.01	.12	.06	.23	.00	.10
HeatingSF	.03	.01	-.01	.02	.00	-.01	-.02	.01	.00
CoolingSF	.06	-.01	.04	-.02	.00	.03	.01	-.02	-.02
OverhangL	-.03	-.02	-.02	-.02	-.03	-.02	-.01	-.03	-.02
ACH50	.04	.05	.00	.03	.03	.02	.03	.01	.01
WaterHeaterE	.00	-.01	-.01	-.02	-.02	-.02	-.03	-.02	-.03
HeatingE	-.03	.55	.00	.00	.02	-.03	-.01	.02	.01
CoolingE	-.01	.01	-.09	.01	-.01	.00	.01	-.01	-.02
HeatingSP	-.02	.02	-.03	.01	.00	.04	.04	.01	.01
CoolingSP	-.05	-.03	-.01	.01	.02	.01	.02	.02	.03
ExtWallU	-.01	-.02	.00	.05	-.01	.00	-.01	-.01	-.01
ExtDoorU	.01	.01	.01	.01	.02	.01	.01	.02	.02

Note: explanation of input names can be found in the main text.

Table 9.1-2. Relationship between difference in building stage emissions for wood versus concrete archetypes and continuous inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
ls	.01	.03	.05	.01	.01	.03	.03	.00	-.01
LivingArea	.08	.08	.07	-.39	-.65	.01	.01	.36	.38
Bedrooms	.02	-.02	.03	-.01	-.01	-.03	-.03	-.01	-.01
Stories	.05	.17	.06	-.35	-.59	.02	.02	.54	.54
AspectRatio	.02	.02	.01	-.02	-.05	-.01	.00	-.02	-.02
DegreeFromS	.01	.00	.04	.01	.01	-.02	-.02	-.01	-.01
RoofPitch	.00	-.02	.02	-.05	-.08	.00	.00	.03	.02
FrontWWR	-.09	.01	-.02	.05	.06	.01	.01	-.06	-.08
BackWWR	-.08	.02	.00	.04	.06	-.02	-.02	-.06	-.07
SideWWR	-.02	.00	.00	.00	.01	.02	.02	.01	.02
SlabU	-.03	.03	.00	.00	-.01	-.01	-.01	.11	.10
RoofU	.04	.03	.02	.01	-.01	.00	-.01	-.06	-.01
WinU	-.02	.00	.02	-.01	.00	.02	.01	-.01	.06
WinSHGC	-.01	-.01	.03	-.02	-.02	.01	.01	.01	.07
HeatingSF	.01	.02	.00	-.02	-.01	-.02	-.02	.00	.00
CoolingSF	.00	.01	.03	.02	-.01	-.03	-.03	-.01	.00
OverhangL	.03	.00	-.01	.02	.03	-.02	-.02	.00	.00
ACH50	.02	.04	.02	-.02	-.03	-.03	-.03	.00	.00
WaterHeaterE	-.02	-.02	.00	.02	.01	.00	.00	.00	-.01
HeatingE	.04	.00	.01	.02	-.01	-.01	-.01	.00	.00
CoolingE	.00	.03	.05	.00	.00	-.04	-.04	.02	.01
HeatingSP	-.01	.03	.00	.01	.02	-.02	-.02	.00	.00
CoolingSP	-.04	-.18	-.10	.00	-.02	.01	.01	-.02	-.02
delExtWallU	-.27	-.37	-.40	.16	.06	.04	.04	.02	.02
ExtDoorU	-.01	.00	-.01	.01	.00	-.01	-.01	.00	.00

Note: explanation of input names can be found in the main text; ‘del’ indicates the difference in U-value of the exterior wall core.

Table 9.1-3. Relationship between difference in building stage emissions for masonry versus concrete archetypes and continuous inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
ls	.07	.09	.13	.02	.02	-	-	.00	-.01
LivingArea	.14	.13	.15	-.10	-.50	-	-	.42	.46
Bedrooms	-.03	-.03	.01	.00	-.01	-	-	-.02	-.02
Stories	.08	.32	.08	-.08	-.45	-	-	.60	.55
AspectRatio	.00	.05	-.02	.01	-.03	-	-	-.02	-.02
DegreeFromS	-.01	-.02	.03	.00	.01	-	-	-.01	-.01
RoofPitch	.02	-.01	.05	.00	-.05	-	-	.03	.04
FrontWWR	-.09	.04	.01	.00	.03	-	-	-.06	-.07
BackWWR	-.11	.03	-.01	.01	.02	-	-	-.05	-.06
SideWWR	-.02	-.03	.02	-.01	.00	-	-	.02	.01
SlabU	-.01	.08	-.03	.01	-.01	-	-	.11	.07
RoofU	.06	.01	.04	.00	-.02	-	-	-.01	.02
WinU	-.04	-.07	.01	.00	-.02	-	-	-.01	.07
WinSHGC	-.05	-.09	.00	.01	-.02	-	-	.02	.09
HeatingSF	-.02	.02	-.03	-.01	.00	-	-	.00	-.01
CoolingSF	.01	.01	.08	.03	-.01	-	-	.00	.01
OverhangL	.07	.02	.04	.03	.03	-	-	.00	.00
ACH50	.01	.08	-.01	-.02	-.04	-	-	.01	.00
WaterHeaterE	-.01	-.04	.01	.02	.02	-	-	-.01	-.01
HeatingE	.06	-.08	.00	.00	-.03	-	-	-.01	-.01
CoolingE	.00	.06	.10	-.03	.01	-	-	.02	.02
HeatingSP	.00	.00	.01	-.01	.01	-	-	.00	.01
CoolingSP	-.04	-.28	-.19	-.01	-.02	-	-	.00	.00
delExtWallU	-.06	-.06	-.10	.11	-.02	-	-	.01	.00
ExtDoorU	.02	.00	.02	-.01	.02	-	-	-.01	.01

Note: explanation of input names can be found in the main text; ‘del’ indicates the difference in U-value of the exterior wall core; difference in replacement emissions for masonry versus concrete archetypes is equal to zero.

Table 9.1-4. Relationship between difference in building stage emissions for wood versus masonry archetypes and continuous inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
ls	-.05	-.09	-.10	-.01	.00	.03	.03	-.01	-.01
LivingArea	-.12	-.11	-.14	-.33	-.34	.01	.01	-.32	-.41
Bedrooms	.04	.04	.00	.01	.00	-.03	-.03	.03	.02
Stories	-.07	-.27	-.07	-.31	-.30	.02	.02	-.45	-.38
AspectRatio	.00	-.04	.02	-.04	-.03	-.01	.00	.01	.01
DegreeFromS	.01	.02	-.02	.00	.01	-.02	-.02	.01	.00
RoofPitch	-.02	-.01	-.05	-.06	-.07	.00	.00	-.02	-.05
FrontWWR	.07	-.05	-.02	.04	.05	.01	.01	.03	.04
BackWWR	.10	-.02	.01	.04	.05	-.02	-.02	.00	.01
SideWWR	.02	.04	-.02	.00	.02	.02	.02	-.01	.00
SlabU	.00	-.06	.03	-.01	.01	-.01	-.01	-.08	.00
RoofU	-.06	-.01	-.03	.00	.00	.00	-.01	-.06	-.04
WinU	.03	.06	-.02	-.01	.01	.02	.01	.00	-.06
WinSHGC	.05	.08	-.01	-.03	-.01	.01	.01	-.02	-.07
HeatingSF	.03	-.02	.03	-.01	-.01	-.02	-.02	.00	.00
CoolingSF	-.02	.00	-.08	-.01	-.02	-.03	-.03	-.01	-.01
OverhangL	-.07	-.03	-.04	.00	.02	-.02	-.02	-.01	.00
ACH50	-.01	-.07	.02	-.01	.01	-.03	-.03	.00	.00
WaterHeaterE	.01	.04	.00	.01	-.02	.00	.00	.00	.00
HeatingE	-.05	.10	.01	.03	.03	-.01	-.01	.03	.02
CoolingE	.00	-.05	-.10	.01	-.02	-.04	-.04	-.01	-.02
HeatingSP	.00	.01	-.01	.02	.01	-.02	-.02	-.01	.00
CoolingSP	.03	.23	.14	.00	.00	.01	.01	-.01	-.01
delExtWallU	-.16	-.18	-.25	.17	.12	.03	.03	.02	-.01
ExtDoorU	-.02	-.02	-.04	.02	-.02	-.01	-.01	.02	-.01

Note: explanation of input names can be found in the main text; ‘del’ indicates the difference in U-value of the exterior wall core.

Table 9.1-5. Relationship between building stage emissions for concrete archetypes and categorical inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
rsgab	.01	-.01	-.01	.12	.14	.03	.02	.02	.02
rship	-.01	.01	.01	-.12	-.14	-.03	-.02	-.02	-.02
rda6d	.01	.01	.00	-.01	-.01	.00	.01	-.04	-.03
rda8d	-.01	-.01	.00	.00	.00	.00	-.01	.01	.01
rda8s	-.01	.00	.00	.02	.01	.00	.00	.02	.02
tnail	.01	.00	.01	.01	.01	.02	.02	-.01	-.01
strap	-.01	.00	-.01	-.01	-.01	-.02	-.02	.01	.01
shtys	.01	-.01	.01	.01	.03	.01	.00	-.43	-.45
shtno	-.01	.01	-.01	-.01	-.03	-.01	.00	.43	.45
gdnod	.00	.00	.00	-.02	-.02	.00	.02	.20	.22
gdwkd	.00	.00	.01	-.01	-.01	.01	.01	.14	.14
gdstd	-.01	.00	-.02	.02	.00	-.01	-.03	.13	.13
gdno2	.02	.01	.02	.01	.02	.02	.01	-.28	-.29
gdsup	-.01	-.02	-.01	.01	.02	-.01	-.01	-.28	-.30
rmfys	.01	-.02	.00	.00	-.01	.00	.00	.04	.03
rmfno	-.01	.02	.00	.00	.01	.00	.00	-.04	-.03
rcbur	.00	.01	.00	-.02	-.02	.00	.00	-.03	-.04
rcspm	.00	-.01	.00	.02	.02	.00	.00	.03	.04
widdA	.02	.00	.02	.03	.03	.01	.02	.21	.23
widdB	-.01	.01	-.02	-.01	-.01	-.02	-.01	.27	.29
widdC	.01	.02	.02	-.01	.00	.03	.01	.01	.01
widdD	-.02	-.03	.00	.00	-.01	-.02	-.02	-.55	-.59

Note: explanation of input names can be found in the main text.

Table 9.1-6. Relationship between difference in building stage emissions for wood versus concrete archetypes and categorical inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
rsgab	.01	.00	.00	-.15	-.27	.01	.01	.12	.13
rship	-.01	.00	.00	.15	.27	-.01	-.01	-.12	-.13
rda6d	.02	-.01	.00	-.01	-.01	-.02	-.02	.15	.16
rda8d	.00	.00	-.01	.01	.01	.01	.01	.16	.16
rda8s	-.02	.01	.01	.00	.00	.01	.01	-.28	-.29
tnail	.02	-.03	.00	-.01	.00	.02	.02	.20	.21
strap	-.02	.03	.00	.01	.00	-.02	-.02	-.20	-.21
shtys	.01	.02	.02	.00	-.02	.00	.00	-.31	-.33
shtno	-.01	-.02	-.02	.00	.02	.00	.00	.31	.33
gdnod	.00	.00	.00	.02	.02	.00	.00	.11	.13
gdwkd	.00	.00	-.03	.00	.01	-.01	-.01	.12	.13
gdstd	-.01	-.02	.00	-.02	-.02	.00	.00	.11	.11
gdno2	-.01	.04	-.01	.00	-.02	.00	.00	-.18	-.19
gdsup	.02	-.01	.03	.00	.00	.01	.01	-.22	-.23
rmfys	.01	-.02	.01	.03	.01	-.03	-.03	.00	-.01
rmfno	-.01	.02	-.01	-.03	-.01	.03	.03	.00	.01
rcbur	.01	.01	.01	.02	.01	.01	.01	.02	.01
rcspm	-.01	-.01	-.01	-.02	-.01	-.01	-.01	-.02	-.01
widdA	.00	.00	.00	-.02	-.02	.02	.02	-.11	-.12
widdB	.00	-.02	.00	.02	.02	.00	.00	-.06	-.05
widdC	-.01	.00	.01	.00	-.02	-.02	-.02	.04	.03
widdD	.01	.02	-.01	-.01	.01	.01	.01	.13	.13

Note: explanation of input names can be found in the main text.

Table 9.1-7. Relationship between difference in building stage emissions for masonry versus concrete archetypes and categorical inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
rsgab	.04	.03	.02	-.02	-.20	-	-	.21	.22
rship	-.04	-.03	-.02	.02	.20	-	-	-.21	-.22
rda6d	.01	.00	.01	.00	-.01	-	-	.14	.15
rda8d	.00	-.01	.02	.00	.01	-	-	.17	.17
rda8s	-.01	.01	-.02	-.01	.00	-	-	-.29	-.29
tnail	.00	-.01	-.01	.00	.01	-	-	.19	.19
strap	.00	.01	.01	.00	-.01	-	-	-.19	-.19
shtys	.00	-.01	.01	-.02	-.03	-	-	-.30	-.34
shtno	.00	.01	-.01	.02	.03	-	-	.30	.34
gdnod	-.01	.01	.00	.01	.04	-	-	.15	.18
gdwkd	.00	.00	-.01	.01	.00	-	-	.09	.09
gdstd	.01	-.01	.00	-.01	-.01	-	-	.09	.10
gdno2	.01	.02	.01	-.02	-.02	-	-	-.18	-.21
gdsup	.00	-.02	.01	.00	-.02	-	-	-.20	-.23
rmfys	.01	-.02	.01	.01	.01	-	-	.01	.01
rmfno	-.01	.02	-.01	-.01	-.01	-	-	-.01	-.01
rcbur	-.02	.00	.00	.01	-.01	-	-	.01	.00
rcspm	.02	.00	.00	-.01	.01	-	-	-.01	.00
widdA	.00	.00	.01	.01	-.01	-	-	-.07	-.07
widdB	.03	-.01	.01	-.02	.01	-	-	-.05	-.03
widdC	-.03	.02	.00	.01	-.02	-	-	.03	.03
widdD	.00	-.02	-.01	.01	.01	-	-	.09	.08

Note: explanation of input names can be found in the main text; difference in replacement emissions for masonry versus concrete archetypes is equal to zero.

Table 9.1-8. Relationship between difference in building stage emissions for wood versus masonry archetypes and categorical inputs; Spearman rank correlation coefficient.

	Energy Usage			Intl. Cnst.		Replacement		Hazard Repairs	
	Cooling	Heating	Other	A	C	A	C	A	C
rsgab	-.04	-.03	-.02	-.16	-.16	.01	.01	-.22	-.22
rship	.04	.03	.02	.16	.16	-.01	-.01	.22	.22
rda6d	-.02	-.01	-.02	-.02	.00	-.02	-.02	-.10	-.10
rda8d	.00	.00	-.02	.02	-.01	.01	.01	-.11	-.13
rda8s	.02	.00	.03	.00	.01	.01	.01	.19	.21
tnail	.01	.00	.01	-.02	-.02	.02	.02	.02	.05
strap	-.01	.00	-.01	.02	.02	-.02	-.02	-.02	-.05
shtys	.00	.01	.00	.01	.02	.00	.00	.19	.23
shtno	.00	-.01	.00	-.01	-.02	.00	.00	-.19	-.23
gdnod	.01	-.01	-.01	.00	-.01	.00	.00	-.12	-.14
gdwkd	.01	.00	.01	-.01	.01	-.01	-.01	-.03	-.03
gdstd	-.01	.01	.00	-.01	-.02	.00	.00	-.05	-.07
gdno2	-.01	.00	.00	.02	.00	.00	.00	.13	.16
gdsup	.01	.02	-.01	-.01	.02	.01	.01	.12	.14
rmfys	-.01	.02	-.01	.02	-.01	-.03	-.03	.00	-.02
rmfno	.01	-.02	.01	-.02	.01	.03	.03	.00	.02
rcbur	.02	.00	.01	.01	.02	.01	.01	.00	.02
rcspm	-.02	.00	-.01	-.01	-.02	-.01	-.01	.00	-.02
widdA	-.01	.00	-.01	-.03	-.01	.02	.02	-.02	-.01
widdB	-.03	-.01	-.01	.03	.02	.00	.00	.02	.02
widdC	.03	-.02	.00	.00	-.01	-.02	-.02	.00	.00
widdD	.00	.03	.02	-.01	-.01	.01	.01	.00	-.01

Note: explanation of input names can be found in the main text.

9.2 Additional Figures

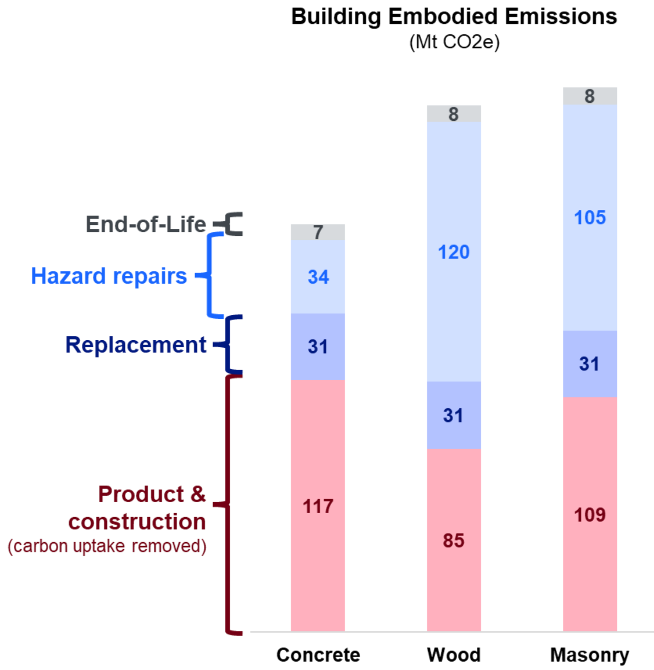

Figure 9.2-1. Building embodied emissions for an example Census Tract in Miami-Dade, FL; mean of 5,000 actualizations, median scenario of 100 wind loading scenarios.

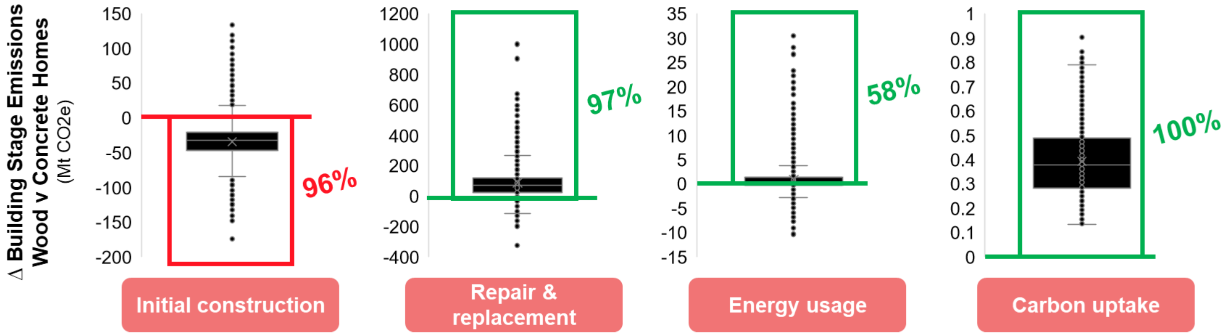

Figure 9.2-2. Building stage emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, median scenario of 100 wind loading scenarios.

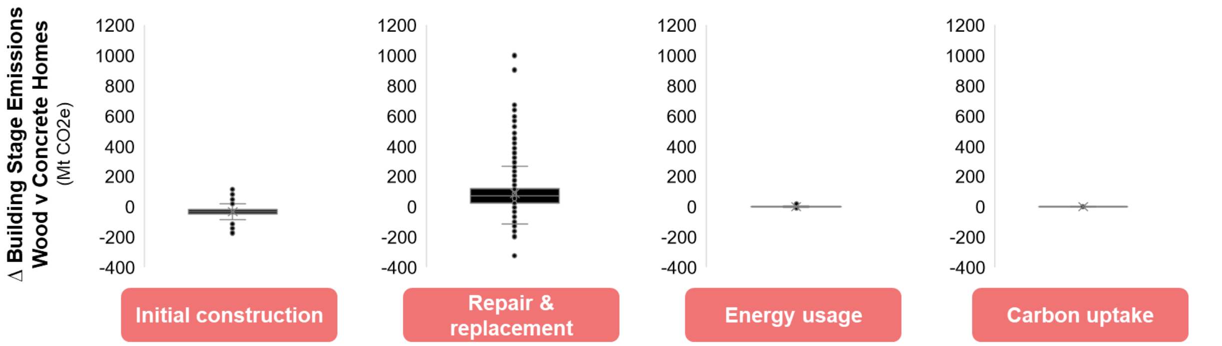

Figure 9.2-3. Building stage emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, median scenario of 100 wind loading scenarios.

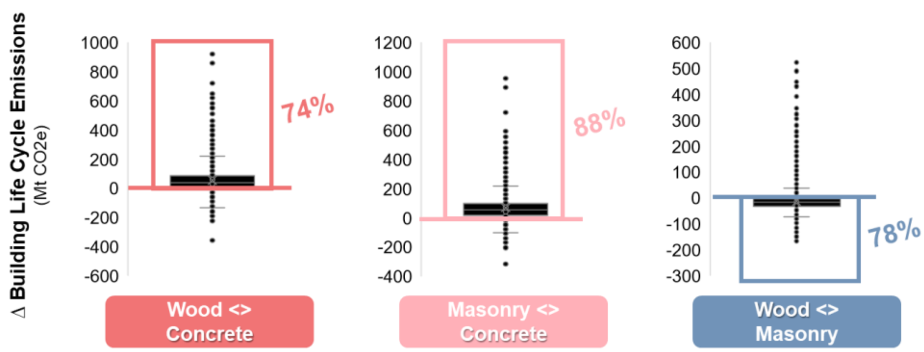

Figure 9.2-4. Building life cycle emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, median scenario of 100 wind loading scenarios.

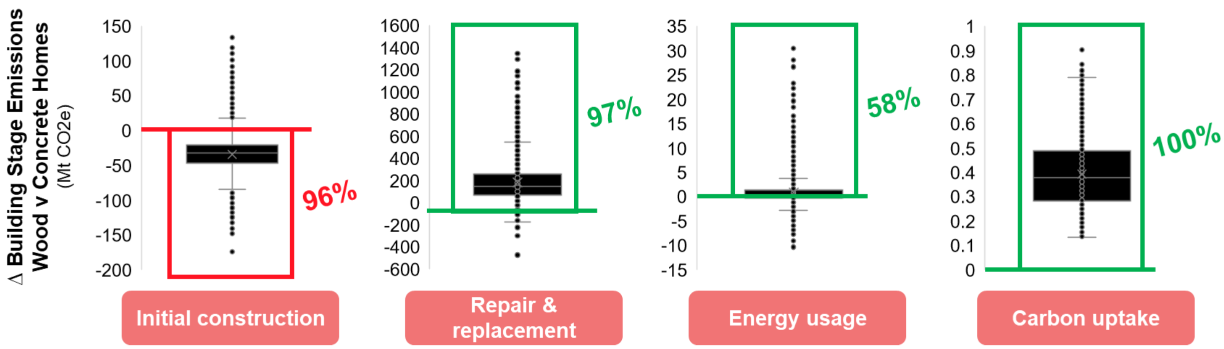

Figure 9.2-5. Building stage emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, 95th-percentile scenario of 100 wind loading scenarios.

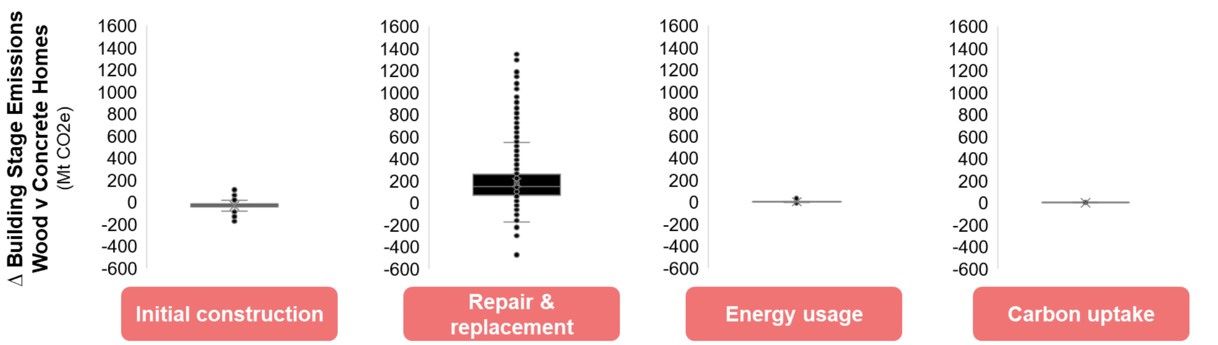

Figure 9.2-6. Building stage emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, 95th-percentile scenario of 100 wind loading scenarios.

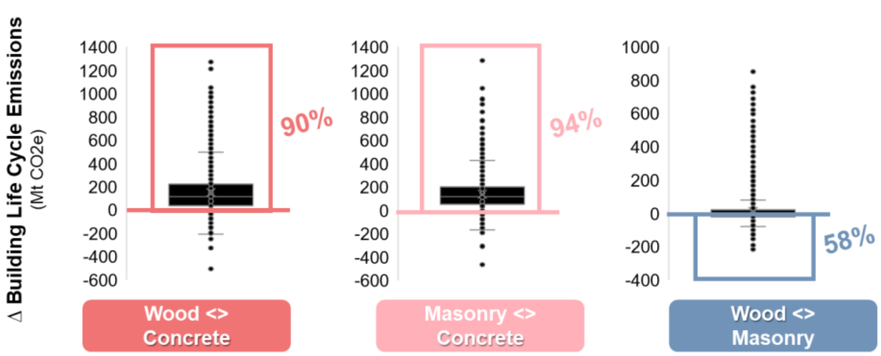

Figure 9.2-7. Building life cycle emissions for an example Census Tract in Miami-Dade, FL; 5,000 actualizations, 95th-percentile scenario of 100 wind loading scenarios.

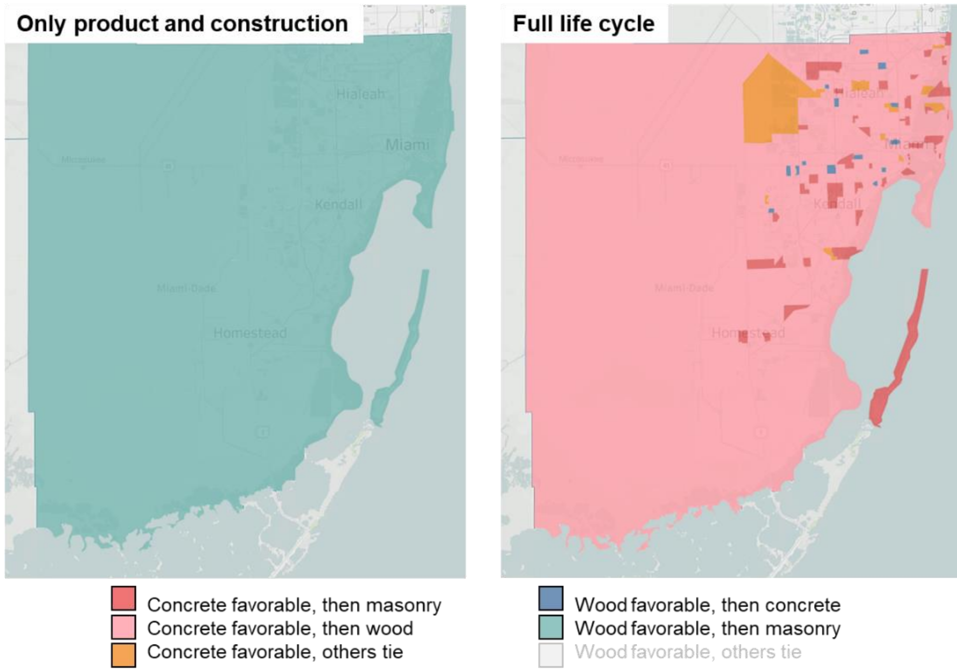

Figure 9.2-8. Exterior wall core material comparisons based on building life cycle emissions in Miami-Dade, FL; $p < .05$ across 5,000 actualizations, median scenario of 100 wind loading scenarios.

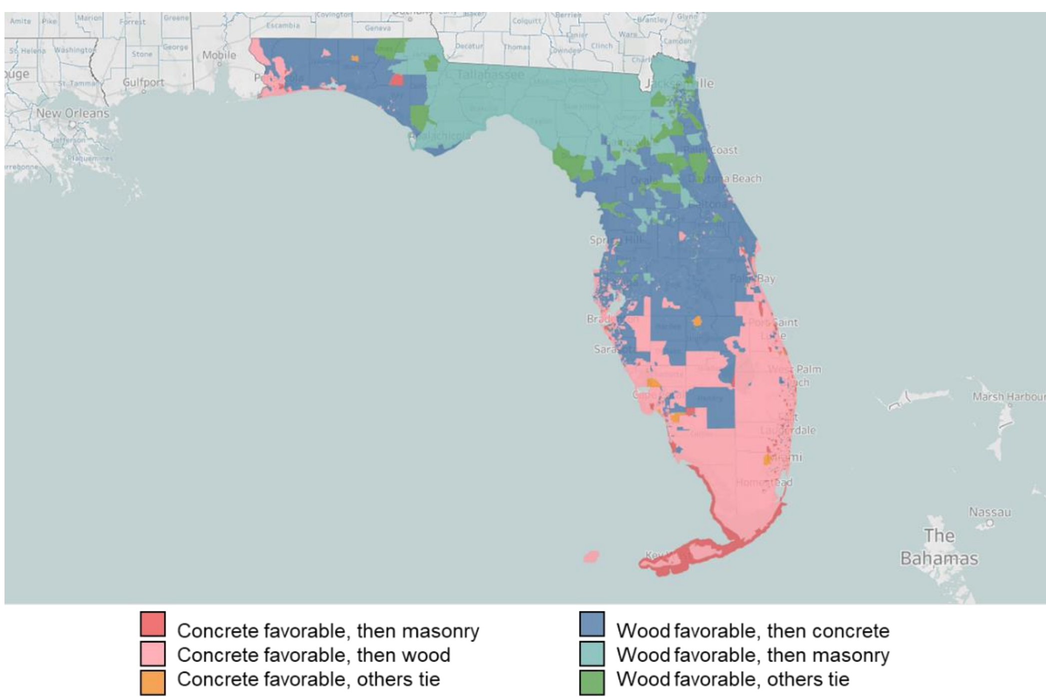

Figure 9.2-9. Exterior wall core material comparisons based on building life cycle emissions in Florida; $p < .05$ across 5,000 actualizations, median scenario of 100 wind loading scenarios.

10 Chapter 5 Supplementary Materials

10.1 Additional Tables

Table 10.1-1. An organization's emission scopes and categories (GHGP, 2011, 2015).

Emission Scope	Emission Category	Required to Report?
Scope 1; direct emissions	• Process emissions associated with operations • Emissions associated with combustion of fuels, including fuels used for operations, on-site power generation, and on-site and off-site transport involving owned ICEVs	**Required by GHGP**
Scope 2; indirect emissions associated with generation of purchased electricity	• Emissions associated with combustion of fuels for generation of purchased electricity, including electricity purchased for operations, on-site power generation, and on-site and off-site transport involving owned EVs	**Required by GHGP**
Upstream scope 3; indirect emissions upstream of the organization's activities	• **Category 1**; cradle-to-gate emissions associated with purchased goods and services	**Required by GHGP**
	• **Category 2**; cradle-to-gate emissions associated with capital goods	
	• **Category 3**; cradle-to-gate emissions associated with fuel- and energy-related activities	
	• **Category 4**; scope 1-2 emissions associated with upstream T&D	**Required by GHGP**; optional to report cradle-to-gate emissions associated with relevant vehicles, facilities, and infrastructure
	• **Category 5**; scope 1-2 emissions associated with waste generated in operations	
	• **Category 6**; scope 1-2 emissions associated with business travel	
	• **Category 7**; scope 1-2 emissions associated with employee commuting	
	• **Category 8**; scope 1-2 emissions associated with upstream leased assets	
Downstream scope 3; indirect emissions downstream of the organization's activities	• **Category 9**; scope 1-2 emissions associated with downstream T&D	**Required by GHGP**; optional to report cradle-to-gate emissions associated with relevant vehicles, facilities, and infrastructure
	• **Category 10**; scope 1-2 emissions associated with processing of sold products	
	• **Category 11**; scope 1-2 emissions associated with use of sold products	
	• **Category 12**; scope 1-2 emissions associated with end-of-life of sold products	
	• **Category 13**; scope 1-2 emissions associated with downstream leased assets	
	• **Category 14**; scope 1-2 emissions associated with franchises	
	• **Category 15;** scope 1-2 emissions associated with investments	

Note: ICEV = internal combustion engine vehicle, EV = electrical vehicle.

Table 10.1-2. A cement producer's emission scopes and categories (WBCSD, 2011b, 2011a).

Emission Scope	Emission Category	Required to Report?
Scope 1; direct emissions	• Process emissions associated with combustion of organic carbon in raw materials and calcination of raw meal, bypass dust, and cement kiln dust • Emissions associated with combustion of fuels, including fuels used for kiln and non-kiln activities, on-site power generation, and on-site and off-site transport involving owned ICEVs	**Required by WBCSD**; optional to report off-site transport involving owned ICEVs
Scope 2; indirect emissions associated with generation of purchased electricity	• Emissions associated with combustion of fuels for generation of purchased electricity, including electricity purchased for kiln and non-kiln activities, on-site power generation, and on-site and off-site transport involving owned EVs	**Required by WBCSD**; optional to report off-site transport involving owned EVs
Upstream scope 3; indirect emissions upstream of the organization's activities	• **Category 1**; cradle-to-gate emissions associated with purchased goods and services, such as clinker, raw materials (e.g. limestone), cement constituents (e.g. non-calcinated limestone), equipment parts, lubricants, fluids, chemical agents, maintenance services	**Required by WBCSD**
	• **Category 2**; cradle-to-gate emissions associated with capital goods, such as kilns, grinders, silos, engines, vehicles, heavy duty materials (e.g. pipes), IT equipment	NOT required by WBCSD; noted as "relevant" but "insignificant"
	• **Category 3**; cradle-to-gate emissions associated with fuel- and energy-related activities	**Required by WBCSD**
	• **Category 4**; scope 1-2 emissions associated with upstream T&D	
	• **Category 5**; scope 1-2 emissions associated with waste generated in operations	NOT required by WBCSD; noted as "irrelevant"
	• **Category 6**; scope 1-2 emissions associated with business travel	NOT required by WBCSD; noted as "relevant" but "negligible"
	• **Category 7**; scope 1-2 emissions associated with employee commuting	
	• **Category 8**; scope 1-2 emissions associated with upstream leased assets	NOT required by WBCSD; noted as "irrelevant"
Downstream scope 3; indirect emissions downstream of the organization's activities	• **Category 9**; scope 1-2 emissions associated with downstream T&D	**Required by WBCSD**
	• **Category 10**; scope 1-2 emissions associated with processing of sold products, such as turning cement into concrete or mortar	NOT required by WBCSD; noted as "difficult to measure for intermediate products"
	• **Category 11**; scope 1-2 emissions associated with use of sold products, such as buildings and roads	
	• **Category 12**; scope 1-2 emissions associated with end-of-life of sold products, such as buildings and roads	
	• **Category 13**; scope 1-2 emissions associated with downstream leased assets	NOT required by WBCSD; noted as "irrelevant"
	• **Category 14**; scope 1-2 emissions associated with franchises	
	• **Category 15;** scope 1-2 emissions associated with investments	

Note: ICEV = internal combustion engine vehicle, EV = electrical vehicle.

Table 10.1-3. Examples of stakeholder activities.

Relevance to Cement Sector	Stakeholder	Activity
In scope, indirect; contribute to upstream scope 3 emissions	Producer of capital goods	Production of capital goods
	Raw material supplier e.g. limestone quarry	Extraction and processing of raw materials
	Fuel supplier e.g. gas company	Extraction and processing of fuels
	T&D provider	T&D of capital goods, raw materials, and fuels
In scope, direct; contribute to scope 1 emissions	Cement producer	Clinker production
In scope, indirect; contribute to scope 2 emissions	Electricity provider	Generation of purchased electricity
In scope, indirect; contribute to downstream scope 3 emissions	Producer of CBPs, or primary, materials (e.g. ready-mixed concrete plant)	Processing of clinker into CBPs
	T&D provider	T&D of CBPs
	Construction company	Installation of CBPs in buildings
	End-user	Use of end-use applications, as pertaining to CBPs (including carbon uptake)
	Waste processor	End-of-life of end-use applications, as pertaining to CBPs (including carbon uptake)
Out of scope	Producers of non-CBP primary materials used in cement's value chain	n/a
	Producers of competing primary materials (e.g. logging company)	n/a

Note: T&D = transportation and distribution, CBP = cement-based product; not meant to be comprehensive.

Table 10.1-4. A building's life cycle stages and activities (Hester, 2018).

<table>
<tr><th>Life Cycle Stage</th><th>Life Cycle Activity</th><th>Emissions</th></tr>
<tr><td rowspan="3">A1-3: material production</td><td>A1: production of capital goods, raw materials, fuels, and electricity</td><td>Cradle-to-gate emissions associated with:
• Clinker used for production of CBPs
• Materials that are NOT clinker but used for production of CBPs
• Materials used for production of non-CBP materials</td></tr>
<tr><td>A2: transport of capital goods, raw materials, fuels, and electricity</td><td>T&D emissions associated with:
• Clinker used for production of CBPs
• Materials that are NOT clinker but used for production of CBPs
• Materials used for production of non-CBP materials</td></tr>
<tr><td>A3: transformation of raw materials into primary materials</td><td>Scope 1-2 emissions associated with:
• Production of CBPs (including carbon uptake of cement wastage)
• Production of non-CBP materials</td></tr>
<tr><td rowspan="2">A4-5: construction</td><td>A4: transport of primary materials</td><td>T&D emissions associated with:
• CBPs
• Non-CBP materials</td></tr>
<tr><td>A5: installation of primary materials in building</td><td>Scope 1-2 emissions associated with:
• Installation of CBPs (including carbon uptake)
• Installation of non-CBP materials</td></tr>
<tr><td rowspan="7">B1-6: use</td><td>B1: use of installed primary materials</td><td>Scope 1-2 emissions associated with:
• Use of CBPs (including carbon uptake)
• Use of non-CBP materials</td></tr>
<tr><td>B2: maintenance of building</td><td rowspan="4">A1-5 emissions associated with:
• CBPs
• Non-CBP materials</td></tr>
<tr><td>B3: repair of building</td></tr>
<tr><td>B4: replacement of building</td></tr>
<tr><td>B5: refurbishment of building</td></tr>
<tr><td>B6: operational energy usage of building</td><td>Scope 1-2 emissions associated with:
• Baseline energy usage
• 'Excess' energy usage</td></tr>
<tr><td>B7: operational water usage of building</td><td>n/a</td></tr>
<tr><td rowspan="4">C1-4: end-of-life</td><td>C1: demolition of building</td><td rowspan="4">Scope 1-2 emissions associated with:
• End-of-life of CBPs (including carbon uptake)
• End-of-life of non-CBP materials</td></tr>
<tr><td>C2: transport of demolished materials</td></tr>
<tr><td>C3: processing of demolished materials</td></tr>
<tr><td>C4: disposal of demolished materials</td></tr>
</table>

Note: T&D = transportation and distribution, CBP = cement-based product.

10.2 Additional Figures

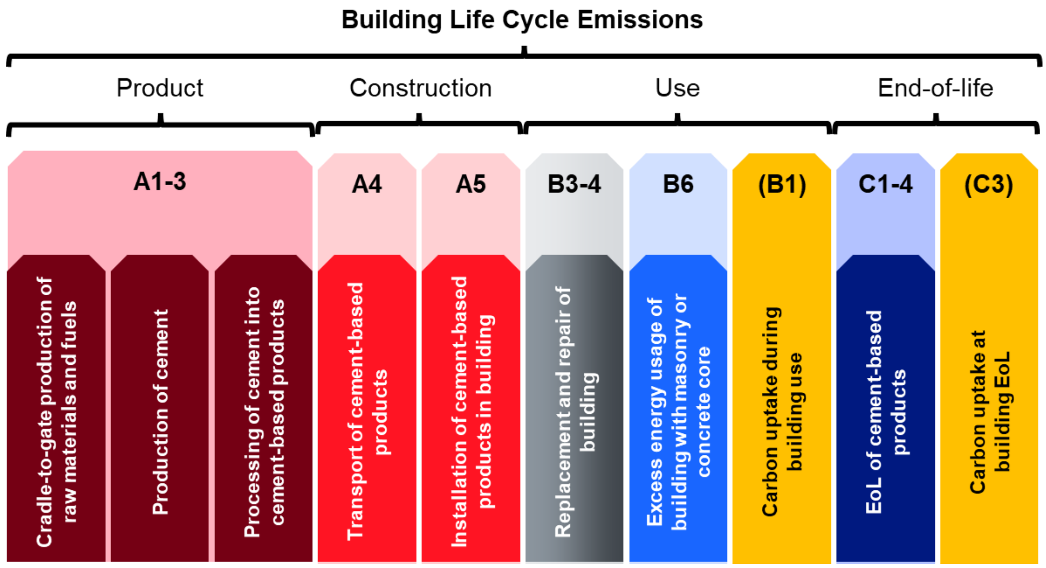

Figure 10.2-1. Outline of how building life cycle emissions map onto cement's sectoral emissions; all building life cycle stages relevant to cement's value chain, however only a portion of emissions in each building life cycle stage relevant to report in cement's sectoral emissions.

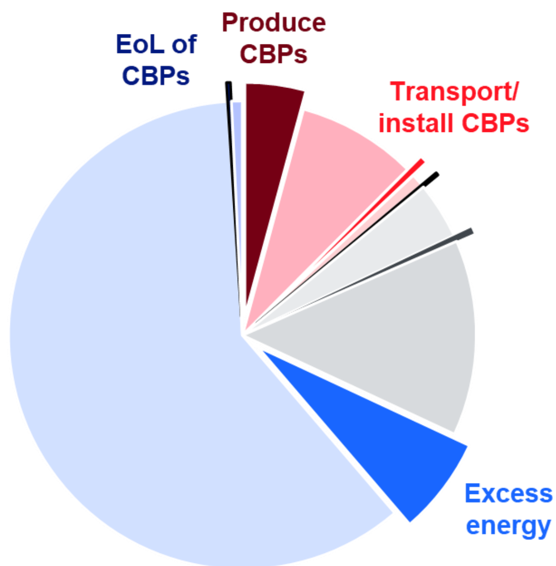

Figure 10.2-2. Breakdown of building life cycle emissions; parts highlight represented emissions which map onto cement's sectoral emissions.

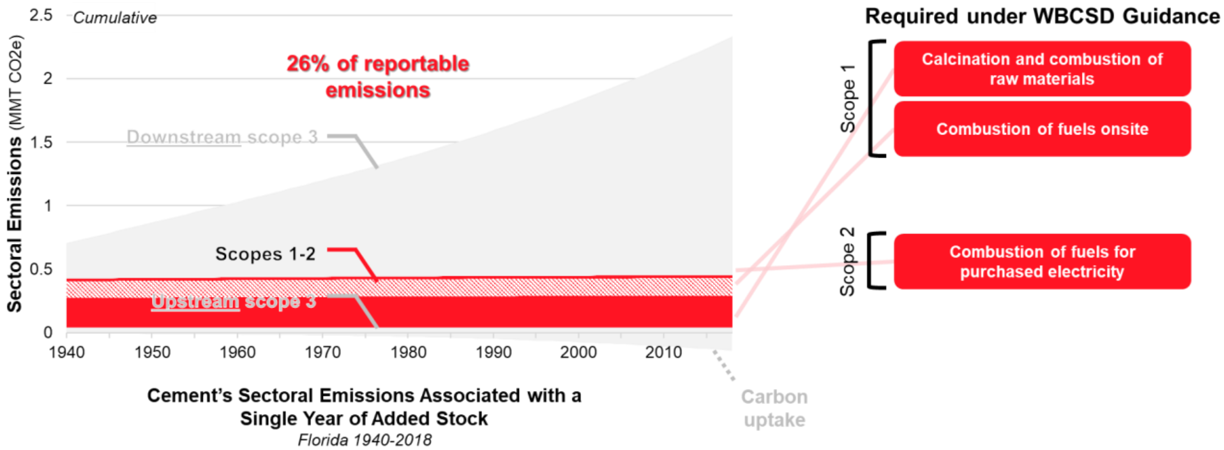

Figure 10.2-3. Reportable emissions associated with cement-based products used in Florida homes built in 1940; parts highlighted represent scopes 1 and 2.

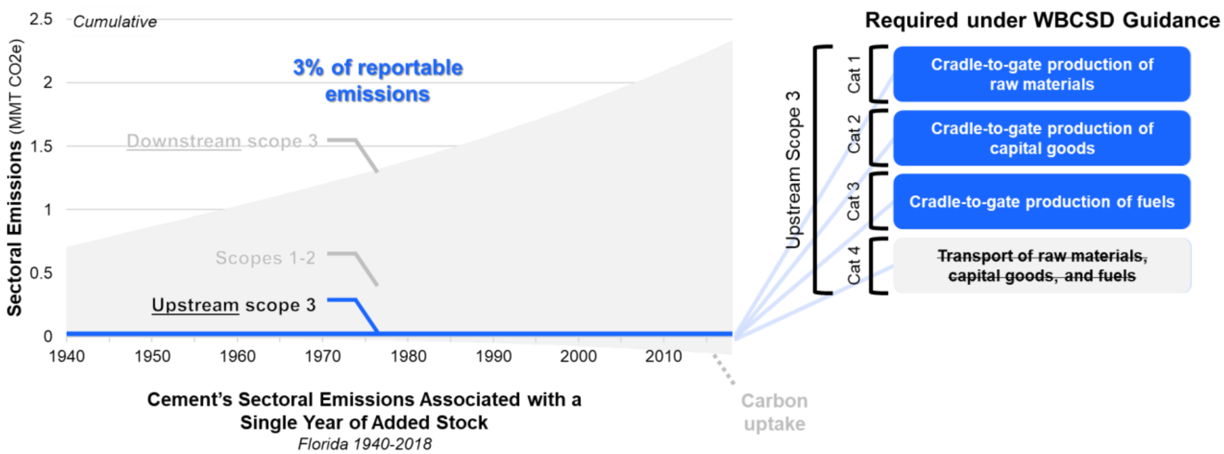

Figure 10.2-4. Reportable emissions associated with cement-based products used in Florida homes built in 1940; parts highlighted represent upstream scopes 3.

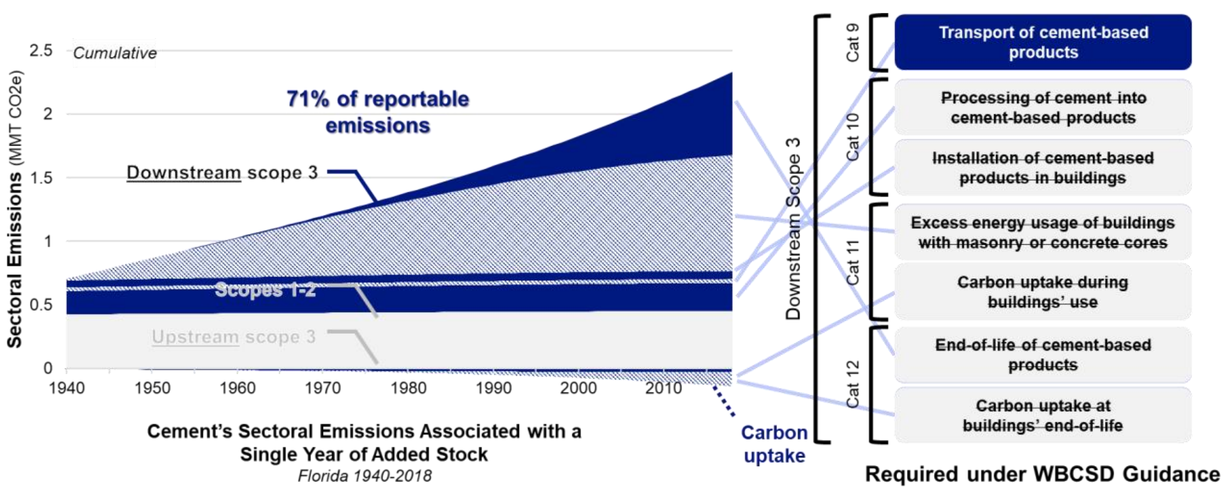

Figure 10.2-5. Reportable emissions associated with cement-based products used in Florida homes built in 1940; parts highlighted represent downstream scopes 3.

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