Texture-Informed Approach for Hurricane Loss Estimation: How Discounting Neighborhood Texture Leads to Under-Valuing Wind Mitigation

by

Ipek Bensu Manav

Bachelor of Science, Civil Engineering
Boğaziçi University, 2018

Submitted to the Department of Civil and Environmental Engineering in Partial Fulfillment of the Requirements for the Degree of Master of Science in Civil and Environmental Engineering at the Massachusetts Institute of Technology

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Signature of Author ............................................................

Department of Civil and Environmental Engineering

May 14, 2021

Certified by .................................................................

Franz-Josef Ulm
Professor of Civil and Environmental Engineering
Thesis Supervisor

Certified by .................................................................

Randolph Kirchain
Principal Research Scientist, Materials Research Laboratory
Co-Supervisor

Accepted by .................................................................

Colette L. Heald
Professor of Civil and Environmental Engineering
Chair, Graduate Program Committee
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ABSTRACT

The focus of emergency management is shifting from response and recovery to pre-disaster mitigation. And, a grand challenge in championing for this shift is effectively communicating natural hazard risks and the value of mitigating structures (to reduce those risks). Present tools for loss estimation overlook building-level variations in wind loading induced by the configuration of surrounding buildings, called neighborhood texture. By doing so, such tools under-estimate expected wind-related losses and under-value wind mitigation – significantly in densely built-up areas susceptible to adverse texture effects. In this thesis, those texture effects are incorporated into a widely recognized loss estimation framework. The impacts of local texture are approximated on the recurrence of wind loads on structures. And, in the case study, the benefits of mitigating are re-evaluated for the residential building stock of the hurricane-prone state of Florida – with a focus on five densely populated counties representing a range of exposure to wind-related hazards. Each home is individually assessed with its prevailing local texture evaluated and its occupancy and building characteristics probabilistically assigned. Mitigation measures considered include shutters, straps, and tie downs. For these mitigation measures, the model results yield annualized benefits of $8.1 billion statewide (80% higher than conventional estimates) ranging from $2.0 billion in Miami-Dade County to $56 million in Duval County (respectively, 90% and 100% higher than conventional estimates).

Thesis Supervisor: Franz-Josef Ulm
Title: Professor of Civil and Environmental Engineering
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CHAPTER 1

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 (National Oceanic and Atmospheric Administration 2020). As costs mount, stakeholders are calling for more focus and spending on proactive, 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 proactive, 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 and Schauer 2006; Peter J. Vickery, Lin, et al. 2006; Peter J. Vickery, Skerlj, et al. 2006) and the Florida Public Hurricane Loss Model (FPHLM) developed by (Hamid et al. 2011). Within such tools, expected wind loads on
a structure derive from the rate of occurrence of storms in its locale and the morphology of its 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 1993; 1992) leading to nearly identical damage and loss risk levels for buildings within the same locale. Previous work by Concrete Sustainability Hub (CSHub) researchers had shown that the fine characteristics of the configuration of surrounding buildings, called neighborhood texture, create local variations in wind loads. Some buildings experience loads far above conventional estimates and some far below (Roxon 2020). This thesis shows that, because structural response is highly non-linear, by ignoring these variations, conventional methods systematically under-estimate expected losses and, therefore, under-value wind mitigation.
CHAPTER 2

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. And, there are two approaches for such models: An empirical approach (fitting claims data to various probability distributions) (Walker 2011), and an engineering-based approach. Engineering-based models span a range of scales from building components (e.g., roof panels and roof-to-wall connections) (Li and Ellingwood 2006), to representative building types (e.g., wood-frame single family dwellings) (Li and van de Lindt 2012), to clusters of representative building types aggregated within a census tract (Peter J. Vickery, Lin, et al. 2006; Peter J. Vickery, Skerlj, et al. 2006), county (Pinelli et al. 2004), or actuarial portfolio (AIR Worldwide 2019; CoreLogic 2019; Risk Management Solutions 2019; Applied Research Associates 2019). These engineering-based models have been incorporated into optimization algorithms for performance-based design (Wen and Kang 2001a; 2001b) and applied in case studies for the lifecycle cost analysis of low-rise (Noshadravan, Miller, and Gregory 2017; Dong and Frangopol 2017; Li 2012) and mid- to high-rise structures (Mahmoud and Cheng 2017).

While a variety of data sources (i.e., field observations, wind tunnel tests, or claims data) and analytical methods have been employed in developing engineering-based
models, all of these models make use of the same American Society of Civil Engineers (ASCE) 7 wind load provisions and, therefore, they all make use of the same guidelines for estimating wind loads on structures. In fact, designers and building officials also make use of these guidelines, because building codes effective in the U.S. also reference the ASCE 7 provisions (ICC 2020; 2019; 2017). For the purposes here, this thesis focuses on one particular aspect in the provisions – the influence of nearby obstructions, such as buildings and vegetation.

Nearby obstructions interfere with wind flows and affect wind loads (or pressures) acting on structures. In the ASCE 7 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

$$q_h \propto K_h v^2$$  \hfill [2.1]

where $q_h$ = velocity pressure at $h$ and $v = 3$-s gust wind speed at the height of 10 m (33 ft) in open terrain (Zhou and Kareem 2002). In literature, $K$ is a continuous function of surface roughness length, $z_0$ (m). And, $z_0$ is derived from the average height and areal density of nearby obstructions (Lettu 1969). Recent studies on the relationship between $K$ and $z_0$ use wind tunnel tests (Ozmen, Baydar, and van Beeck 2016), and Monte Carlo (MC) (Datin and Stedman 2015), finite element (FE) (He, Pan, and Cai...
and computational fluid dynamics (CFD) simulations (Kent et al. 2017; Ricci, Patruno, and de Miranda 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 1993; 1992).

Over the last three decades, since its creation, the ASCE 7 provisions have been revised seven times (Barben and Solnosky 2017). Although changes have been made to the definitions of factors that add onto Equation [2.1] and the wind speeds that Equation [2.1] 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 (Peter J. Vickery and Skerlj 2000) and reintroduction of Exposure D (Peter J. Vickery et al. 2010), and calling for (Irwin 2006) and proposing systematic approaches for assignment (Ellison and Rutz 2015) which currently relies on expert judgment (Ellingwood and Tekie 1999).

Of tools for loss estimation, HAZUS is the basis for large-scale cost-benefit reports (NIBS 2019b). And, it contains the first nationwide database for $z_0$ assigned systematically. This assignment makes use of land use land cover (LULC) maps, where each LULC category corresponds to a $z_0$ value (Peter J. Vickery, Lin, et al. 2006). In HAZUS, terrain is incorporated into damage and loss functions (Peter J. Vickery, Skerlj, 2006).
et al. 2006) developed from wind tunnel tests (Case and Isyumov 1998; Ho, Surry, and Davenport 1992). These wind tunnel tests were conducted on regularly spaced arrays of similar low-rise buildings, and 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 the HAZUS framework, inhomogeneous areas are broken down into relatively homogeneous stretches and then $z_0$ values are averaged (so constant) across the area as a whole (weighted by building footprint exposure) (Peter J. 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. And, as a consequence, current loss estimation tools have limitations in evaluating the influence of surrounding buildings on sustained damage (i.e., through shielding or tunneling) (Pita et al. 2015).

Recently, Roxon et al. demonstrated the use of the radial distribution function (RDF) from statistical mechanics as a computationally tractable method to quantify the impact of inhomogeneity at finer scales (Roxon 2020). This function provides a succinct measure, referred to by Roxon et al. as texture, of disorder in the configuration of surrounding buildings within fetches of only tens of meters. Roxon et al. 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 clusters of 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 Supplemental Materials.)

The literature on loss estimation is extensive. The majority 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 et al.’s texture
represents a computationally inexpensive method to account for local configuration, but
it has not yet been adapted for loss estimation. This thesis aims to fill that gap by
incorporating a texture-based model in a loss estimation framework, and applying that
framework to explore the implications of neighborhood texture on estimates of expected
losses and the derivative value of wind mitigation.

To accomplish this goal, a procedure is introduced for deriving probabilistic, directional
multipliers on wind speeds that approximate the impacts of local configuration, and
these multipliers are incorporated into a widely recognized loss estimation framework –
that of HAZUS. Because no public dataset includes all information needed to carry out
this analysis, occupancy and building characteristics are probabilistically assigned.
To estimate the expected wind-related losses for any building, it is necessary to know its expected wind loads, the buildings occupancy type (e.g., single-family dwelling), and the type of construction (e.g., wood-frame with one story) (Peter J. Vickery, Lin, et al. 2006; Peter J. 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 author is unaware of any publicly available dataset that provides all of this information for individual buildings in the U.S. Instead, the relevant data comes in two forms. Geographic information system (GIS) datasets are available that describe the location and footprint (and occasionally three-dimensional envelop) of buildings in a given area. And, separately, data is available on the prevalence of occupancy and building types (and many other demographic and socioeconomic characteristics) for that area. In the U.S., the highest resolution form of the latter data is available for census tracts, where each census tract averages 4,000 inhabitants and is designed to be homogeneous in regard to population characteristics and living conditions (U.S. Census Bureau, n.d.).

To accommodate the state of the data, the methodology comprises four elements: [1] The use of GIS files to evaluate the local texture for each building in the area of interest, [2] the incorporation of local texture into the recurrence of wind loads acting on each
building, [3] the construction of probability distributions (called building schemes) to describe their structural response from the likelihood of occupancy and building types in the area of interest, and [4] the integration of all this information to estimate expected wind-related structural losses and the benefits of mitigation in reducing those losses.
3.1 *Evaluating Local Texture and Its Impact on Building Drag Coefficients*

To estimate the impacts of neighborhood texture on expected structural losses, we must 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 can 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.

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 the $\sqrt{A_b}$ across all buildings. Using this value, the local neighborhood of $b$ is defined as comprising of buildings within a radius of $10\hat{L}$. For this neighborhood, two characteristics of $b$ are estimated. These are the local areal density, $P_b$ (buildings per m$^2$), and the local density length, $L_b$ (m). Additionally, the number of neighbors, $n_b$, is...
computed as the buildings within a radius 3.5 $L_b$ of $b$. These attributes are then used to
derive the maximum drag coefficient specific to $b$, $C_b$, using a relationship defined in
(Roxon 2020). Formally,

$$C_b = n_b \sqrt{9.5P_bL_b} + 1$$

[3.1.1]

The relationship in Equation [3.1.1] was empirically derived from CFD simulations of
clusters of square-shaped buildings arranged with textural characteristics ($P$, $L$, and $n$)
replicated from real-life cities (Roxon 2020). Conventionally, the drag coefficient of an
isolated square-shaped building, $C_0$, is 2 (“Drag Coefficient” 2004). And, $C_b > C_0$
implies texture-induced amplifications in wind loading and $C_b < C_0$ implies texture-
induced reductions in loading. **Figure 3.1-1** 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 $C$ are for
buildings in locales with high density/low disorder. In **Figure 3.1-1** this occurs within the
southernmost census tract (extensive orange coloration of buildings). And, the greatest
potential reductions in $C$ are for buildings in locales with low density/high disorder. In
**Figure 3.1-1** this occurs within the northernmost highlighted census tract (extensive
blue coloration of buildings). Locales with medium density/medium disorder exhibit a
mix of amplifications and reductions.
Figure 3.1-1. Trends in local texture; Greatest load amplifications for buildings in locales with high density/low disorder, and greatest load reductions for buildings in locales with low density/high disorder.
3.2 Incorporating Texture-Adjusted Drag Coefficients in Wind Loads

In the existing 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; P. J. Vickery et al. 2000; P. J. Vickery, Skerlj, and Twisdale 2000). The provisions also give guidelines on adjusting these basic gusts to local gusts (\( v_b^L \)) based on the prevailing local terrain (in the wind layer interfered by the 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

\[
v_b^L = W v_b^B
\]

where \( W \) is the square-root of the exposure factor, \( K \), from Equation [2.1] (Cook et al. 2011).

To account for the impact of neighborhood texture, we estimate building-specific effective gusts (\( v_b^{\text{eff}} \)). 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 a given \( b \).

Formally, therefore, the relationship between \( v_{b}^{\text{eff}} \) and \( v_{b}^{L} \) is

\[
v_{b}^{\text{eff}} = eW_{b} v_{b}^{L}
\]

where \( eW_{b} \) is a proportionality constant that will be referred to as the effective wind speed ratio.

To estimate expected losses, the HAZUS framework is used which does not explicitly compute local gusts, but rather maps basic gusts to expected damage and losses for five terrain descriptions (and their characteristic roughness length \( z_{0} \)), namely “Open” (\( z_{0} = 0.03 \) m), “Lightly Suburban” (\( z_{0} = 0.15 \) m), “Suburban” (\( z_{0} = 0.35 \) m), “Lightly Treed” (\( z_{0} = 0.70 \)) and “Treed” (\( z_{0} = 1.0 \)) (Peter J. Vickery, Skerlj, et al. 2006). To make use of this framework, losses are estimated based on effective basic gusts (\( v_{b}^{\text{effB}} \)), defined as:

\[
v_{b}^{\text{effB}} = eW_{b} v_{b}^{B}
\]

Equation [3.2.3] implies that for a building in a neighborhood configuration that induces \( eW = 1.2 \), for instance, basic gusts of 100 mph (\( v_{b}^{B} = 100 \) mph) carry the impact of
basic gusts of 120 mph \( v_{\text{b effB}} = 120 \text{ mph} \). By logical extension, in such a context, the impact of 120 mph occurs with the frequency of 100 mph basic gusts. This latter frequency is derived from a Weibull fitting of basic gusts at centroids of census tracts (Martin E. Batts et al. 1980).

Because structural response is highly non-linear, the implications of texture-induced changes vary significantly. Considering 100 mph basic gusts on an unmitigated single-family dwelling in Open terrain, \( eW = 1.2 \) increases expected losses by 14% of replacement cost; whereas, \( eW = 0.8 \) decreases expected losses by only 3% of replacement cost (FEMA 2019).

To develop the relationship expressed in Equation [3.1.1], Roxon et al. repeated CFD simulations for winds impinging on the simulated neighborhoods from each of the four cardinal directions (Roxon 2020). As such, each building had four simulation results including four wind loads and four drag coefficients. These results were ranked by the directional severity, \( d \), of loading, and the ranked set was indexed on \( d \in \{1,2,3,4\} \), where \( d = 4 \) represents the case with the most severe loading. So, \( C_b \) is associated with \( d = 4 \). And, worst-case wind loading is proportional to \( C_b \) times gust wind speed squared.
Therefore, we can discuss the effects of texture either in terms of changes to the drag coefficient (for a given $v_b^B$) or in terms of effective basic gusts ($v_b^{erb}$) that load the structure with a conventional drag coefficient $C_0$. That is to say

$$C_b \nu_b^B \quad = \quad C_0 \nu_b^{erb}$$  \[3.2.4\]

And, using Equation [3.2.4] and the relationship in Equation [3.2.3], we infer

$$C_b \nu_b^B \quad = \quad C_0 \quad eW_b \nu_b^B$$  \[3.2.5\]

This provides a relationship between $eW_b$ and $C_b$. Formally, that is stated as:

$$eW_b^{d=4} = \sqrt{C_b / C_0}$$  \[3.2.6\]

$eW_b^{d=4}$ are modeled as functions of $x$, where $x \in \{1, 2, \ldots, 6\}$, and each $x$ corresponds to a range $\Omega_x$ such that $\Omega_1 = \{1.0 \leq C \leq 1.5\}$, $\Omega_2 = \{1.5 \leq C \leq 2.0\}$, \ldots, $\Omega_6 = \{3.5 \leq C \leq 4.0\}$. These functions are a Gamma fitting for $x = 1$, and a Beta fitting for $x \neq 1$ (Table 3.2-1). For each building, $eW_b^{d=4}$ is computed; expected losses are evaluated in the maximum direction; and, Gamma/Beta functions are derived for the...
inferior directions based on the range $\Omega$ which $C_b$ is found. These latter functions are then placed within convolution integrals to evaluate expected losses in the inferior directions.
Table 3.2-1. Summary of Roxon et al.’s simulation results and distribution fitting.

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</tr>
<tr>
<td></td>
<td>(129)</td>
<td>(3)</td>
<td>(2)</td>
<td>(2)</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>$B_x^{d=1}$</td>
<td>894</td>
<td>10</td>
<td>10</td>
<td>11</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>(144)</td>
<td>(1)</td>
<td>(1)</td>
<td>(1)</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>$d = 2$</td>
<td>0.94</td>
<td>0.87</td>
<td>0.82</td>
<td>0.79</td>
<td>0.77</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.10)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$A_x^{d=2}$</td>
<td>799</td>
<td>27</td>
<td>19</td>
<td>15</td>
<td>11</td>
<td>9</td>
</tr>
<tr>
<td></td>
<td>(129)</td>
<td>(2)</td>
<td>(1)</td>
<td>(1)</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>$B_x^{d=2}$</td>
<td>855</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>(138)</td>
<td>(0.2)</td>
<td>(0.3)</td>
<td>(0.3)</td>
<td>(0.3)</td>
<td></td>
</tr>
<tr>
<td>$d = 3$</td>
<td>0.97</td>
<td>0.93</td>
<td>0.90</td>
<td>0.87</td>
<td>0.87</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.05)</td>
<td>(0.07)</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>$A_x^{d=4}$</td>
<td>1276</td>
<td>18</td>
<td>12</td>
<td>12</td>
<td>9</td>
<td>7</td>
</tr>
<tr>
<td></td>
<td>(206)</td>
<td>(1)</td>
<td>(1)</td>
<td>(1)</td>
<td>(1)</td>
<td></td>
</tr>
<tr>
<td>$B_x^{d=4}$</td>
<td>1317</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>(212)</td>
<td>(1)</td>
<td>(1)</td>
<td>(0.1)</td>
<td>(0.1)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Means, and standard deviations (in parentheses) across observations; $e W_b^d = effective wind speed ratio of observation b for directional severity d; A_x^d = fit parameter (shape if Gamma, alpha (shape) if Beta); B_x^d = fit parameter (rate if Gamma, beta (shape) if Beta).
3.3 Constructing Building Schemes

Publicly available datasets for building footprints, specifically GIS files, either do not include attributional tables for information on occupancy and building type or have sparse attributional tables with limited information on occupancy type only (like that of the OpenStreetMap (OSM) database). This lack of complete information is referred to as under-specification. And, in this thesis, under-specification is addressed by probabilistically assigning occupancy and building types to buildings of which the local texture has been evaluated and the census tract is known. In the HAZUS framework, the mapping of building types is described through building schemes.

Each building could belong to a set of possible occupancy types $i$ (those considered in this thesis listed in Table 3.3-1), and each $i$ could be constructed of a set of possible building types $j$ (listed in Table 3.3-2). The prevalence of occupancy types (i.e., single-family dwelling) can be obtained through recent census data, and that of building types can be obtained through HAZUS building schemes. In HAZUS, each census tract belongs to a schematic region (and a state). Building schemes describe the prevalence of “specific” building types on a regional level and “general” building types on a state level. General building types pertain to construction material (i.e., wood-frame), and specific building types pertain to construction characteristics (i.e., single-family dwelling with one story). HAZUS provides loss functions for each general and specific building
type, and according to whether or not (or which) mitigation measures are applied (listed in Table 3.3-3).
Table 3.3-1. List of occupancy types considered in this thesis.

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>RES1</td>
<td>Single-family dwellings</td>
</tr>
<tr>
<td>RES2</td>
<td>Manufactured homes</td>
</tr>
<tr>
<td>RES3A</td>
<td>Duplexes</td>
</tr>
<tr>
<td>RES3B</td>
<td>Triplexes and quads</td>
</tr>
<tr>
<td>RES3C</td>
<td>Multi-unit housing with 5-9 units</td>
</tr>
<tr>
<td>RES3D</td>
<td>Multi-unit housing with 10-19 units</td>
</tr>
<tr>
<td>RES3E</td>
<td>Multi-unit housing with 20-49 units</td>
</tr>
<tr>
<td>RES3F</td>
<td>Multi-unit housing with 50+ units</td>
</tr>
</tbody>
</table>

Note: Nomenclature for codes borrowed from HAZUS.
### Table 3.3-2. List of building types considered in this thesis.

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

Note: Nomenclature for codes borrowed from HAZUS.
Table 3.3-3. List of mitigation measures considered in this thesis.

<table>
<thead>
<tr>
<th>Code</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MM1</td>
<td>Applying shutters on all windows and entry doors</td>
</tr>
<tr>
<td>MM2</td>
<td>Placing straps or clips on roof-to-wall connections</td>
</tr>
<tr>
<td>MM3</td>
<td>Providing superior wood roof deck attachment</td>
</tr>
<tr>
<td>MM4</td>
<td>Providing superior metal roof deck attachment</td>
</tr>
<tr>
<td>MM5</td>
<td>Providing secondary water resistance</td>
</tr>
<tr>
<td>MM6</td>
<td>Applying tie downs</td>
</tr>
</tbody>
</table>
For the purposes of the study in this thesis, two assumptions were made about occupancy types. First, all buildings were assumed to be residential (though some buildings are commercial). We would 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). Also, building schemes were assumed to apply uniformly across each census tract (though structures of closer proximity are likelier to be similar).
3.4 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 \( m = \mathcal{M} \) respectively), and with and without consideration of local texture (\( t = T \) and \( t = \mathcal{T} \) respectively). More specifically, the expected annual benefits (EAB) (of mitigating) for a building \( b \) are defined as the difference between expected annual losses (EAL) when \( m = \mathcal{M} \) versus \( m = M \). Expressed analytically, that is

\[
EAB_b^i = EAL_b^{i,\mathcal{M}} - EAL_b^{i,M} \tag{3.4.1}
\]

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 \( t = \mathcal{T} \). Formally, this is the additional expected annual benefits (AEAB) for \( b \), and compute it as:

\[
AEAB_b = EAB_b^T - EAB_b^\mathcal{T} \tag{3.4.2}
\]

Referencing the building schemes, EAL for \( b \) is a weighted average of EAL estimated for each occupancy type \( i \) that \( b \) could belong to. And, EAL for each \( i \) is its local
replacement cost times the convolution integral of its loss function over the recurrence of effective basic gusts $v_{b}^{r}$ 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 $z_{0}$ (based on $z_{0}$ of the census tract containing $b$) (Peter J. Vickery, Skerlj, et al. 2006).
CHAPTER 4

CASE STUDY

To demonstrate the application of the modified, texture-informed framework, a case study was produced 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 2019) (Table 4-1). In this section, statewide results are discussed along with results for five focal counties. The 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 2019) (Table 4-1). 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 reside near or on the Gulf coast; and, Miami-Dade, Orange and Duval reside near or on the Atlantic coast (shown in Figure 4-1).
### Table 4-1. Exposure in Florida and focal counties.

<table>
<thead>
<tr>
<th></th>
<th>#Tracts</th>
<th>#Buildings</th>
<th>#Households</th>
</tr>
</thead>
<tbody>
<tr>
<td>Florida</td>
<td>4190</td>
<td>6.90 million</td>
<td>9.25 million</td>
</tr>
<tr>
<td>Miami-Dade</td>
<td>518</td>
<td>495 thousand</td>
<td>1.01 million</td>
</tr>
<tr>
<td>Lee</td>
<td>166</td>
<td>281 thousand</td>
<td>383 thousand</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>319</td>
<td>418 thousand</td>
<td>564 thousand</td>
</tr>
<tr>
<td>Orange</td>
<td>206</td>
<td>353 thousand</td>
<td>518 thousand</td>
</tr>
<tr>
<td>Duval</td>
<td>173</td>
<td>303 thousand</td>
<td>400 thousand</td>
</tr>
</tbody>
</table>

Note: Number of census tracts limited to those identified to contain buildings.
Figure 4-1. Map of maximum effective wind speed ratio; Each mean averaged across buildings in census tract; Orange indicates potential amplifications in worst-case wind loads, while blue indicates potential reductions in worst-case wind loads.
In this study, all building footprints were extracted from an online repository (Microsoft 2018). 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. In the HAZUS database, each census tract has a surface roughness length, $z_0$, and recurrence intervals for basic gust wind speeds, $v^R$. Also, each census tract belongs to a schematic region. In Florida, there are four 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 cost (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 occupancy types are the same as those counted by U.S. Census Bureau’s American Community Survey (ACS). In this thesis, the prevalence of occupancy types in each census tract was taken from the 2018 ACS Selected Housing Characteristics (ACS DP04) (U.S. Census Bureau 2019). The significance of this integration with recent census data (as opposed to simply referring to the HAZUS database for the prevalence of occupancy types) is that it enables future studies to consider the demographic and socioeconomic characteristics of households vulnerable to wind-related losses and texture-induced loss amplifications.
For missing census tract level information, a nearest-neighbors matrix of centroids of census tracts was used. 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.
CHAPTER 5

RESULTS

Applying the relationships in Equation [3.1.1] and Equation [3.2.6], the maximum effective wind speed ratio, $e W^{d=4}$, is estimated for each building in Florida. Figure 4-1 maps the census tract level summary of this estimation (in terms of mean of $e W^{d=4}$ across buildings in each census tract). In Figure 4-1, 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 17% of Florida census tracts (Figure 5-1). Conversely, denser census tracts are cartographically smaller and are associated with potential amplifications (orange on the map). They represent 83% of census tracts (nearly half of which have a mean of $e W^{d=4}$ greater than 1.2) (Figure 5-1). In Florida, these densely built-up areas tend to be along the coastline – where wind-related hazards are already of high concern.
Figure 5-1. Histogram of census tract mean of maximum effective wind speed ratio; Each mean averaged across buildings in census tract; A majority of census tracts have potential amplifications in worst-case wind loads.
In the maximum direction, $d = 4$, $eW_b$ is greater than unity (i.e., texture induces more severe wind loading than a terrain-only model) for 63% of the Florida building stock (of which nearly three-quarters have $eW_b^{d=4}$ greater than 1.2, and nearly half have $eW_b^{d=1}$ greater than 1.4) (Table 5-1). Correspondingly, in the minimum direction, $d = 1$, $eW_b$ is below unity for the entire building stock (and nearly half have $eW_b^{d=1}$ below 0.8) (Table 5-1). The directional average, across $d = 1$ through $d = 4$ for each building, has a mean of 0.98 with a standard deviation of 0.15 (Table 5-1).
Table 5-1. Summary of directional effective wind speed ratios.

<table>
<thead>
<tr>
<th>$e W^d_b$</th>
<th>Directional Severity (d)</th>
<th>Min. (d = 1)</th>
<th>Max. (d = 4)</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>(-∞,0.80)</td>
<td></td>
<td>43%</td>
<td>9%</td>
<td>13%</td>
</tr>
<tr>
<td>[0.80,1.0)</td>
<td></td>
<td>57%</td>
<td>18%</td>
<td>39%</td>
</tr>
<tr>
<td>(1.0)</td>
<td></td>
<td>0%</td>
<td>9%</td>
<td>0%</td>
</tr>
<tr>
<td>(1.0,1.20]</td>
<td></td>
<td>0%</td>
<td>18%</td>
<td>48%</td>
</tr>
<tr>
<td>(1.20,1.40]</td>
<td></td>
<td>0%</td>
<td>17%</td>
<td>0%</td>
</tr>
<tr>
<td>(1.40,∞)</td>
<td></td>
<td>0%</td>
<td>29%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Note: Percentages, means, and standard deviations across buildings; $e W^d_b = \text{effective wind speed ratio of building } b \text{ for directional severity } d$. 
5.1 Implications of Texture Effects on Mitigation Benefits

Based on texture-adjusted expected wind loadings, the model results yield expected annual losses (EAL) with a statewide median of $732 per year per household ($/yr/hh) for an unmitigated building stock ($m = \mathcal{M}$), and $270/yr/hh for a mitigated building stock ($m = \mathcal{M}$) (Table 5.1-1). Comparing $m = \mathcal{M}$ versus $m = M$ (as in [3.4.1]), that yields expected annual benefits (EAB) (of mitigating) which have a statewide median of $468/yr/hh and reach $1,310/yr/hh to $6,720/yr/hh in the upper quartile of Florida census tracts (representing 2.2 million households) (Table 5.1-1). Comparing analyses considering the impact of texture ($t = T$) to one that does not ($t = \mathcal{T}$), the results yield additional expected annual benefits (AEAB) (as defined in [3.4.2]) which have a statewide median of $210/yr/hh and reach $589/yr/hh to $3,300/yr/hh in the upper quartile of Florida census tracts (Table 5.1-1).
Table 5.1-1. Summary of expected annual losses and benefits of mitigating; Statewide.

<table>
<thead>
<tr>
<th></th>
<th>Considering Texture Effects ($t = T$)</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EAL ($m = \mathcal{M}$)</td>
<td>EAL ($m = M$)</td>
<td>EAB</td>
<td>AEAB</td>
</tr>
<tr>
<td>Minimum</td>
<td>$2/yr/hh</td>
<td>$1/yr/hh</td>
<td>$1/yr/hh</td>
<td>-$1,570/yr/hh</td>
</tr>
<tr>
<td>25&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>$336/yr/hh</td>
<td>$139/yr/hh</td>
<td>$196/yr/hh</td>
<td>$22/yr/hh</td>
</tr>
<tr>
<td>50&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>$732/yr/hh</td>
<td>$270/yr/hh</td>
<td>$468/yr/hh</td>
<td>$210/yr/hh</td>
</tr>
<tr>
<td>75&lt;sup&gt;th&lt;/sup&gt; percentile</td>
<td>$1,932/yr/hh</td>
<td>$608/yr/hh</td>
<td>$1,310/yr/hh</td>
<td>$589/yr/hh</td>
</tr>
<tr>
<td>Maximum</td>
<td>$9,470/yr/hh</td>
<td>$2,760/yr/hh</td>
<td>$6,720/yr/hh</td>
<td>$3,300/yr/hh</td>
</tr>
<tr>
<td>Mean (Std. Deviation)</td>
<td>$(1,310/yr/hh)$</td>
<td>$(420/yr/hh)$</td>
<td>$(885/yr/hh)$</td>
<td>$(404/yr/hh)$</td>
</tr>
</tbody>
</table>

Note: Percentiles, means, and standard deviations across averages for census tracts; $m = \mathcal{M}$ = unmitigated building stock; $m = M$ = mitigated building stock.
Among the focal counties, AEAB values are highest in the southernmost, Miami-Dade County, and lowest in the northernmost, Duval County. Miami-Dade has a mean of $909/yr/hh with a standard deviation of $758/yr/hh. Duval has a mean of $70/yr/hh with a standard deviation of $65/yr/hh. And, the other counties average at roughly a couple hundred thousand dollars per year per household (Table 5.1-2).
Table 5.1-2. Summary of expected annual losses and benefits of mitigating; Focal counties.

<table>
<thead>
<tr>
<th>County</th>
<th>EAL ($m = \mathcal{M}$)</th>
<th>EAL ($m = M$)</th>
<th>EAB</th>
<th>AEAB</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miami-Dade</td>
<td>$2,800/yr/hh</td>
<td>$846/yr/hh</td>
<td>$1,950/yr/hh</td>
<td>$909/yr/hh</td>
</tr>
<tr>
<td></td>
<td>($1,420/yr/hh)</td>
<td>($408/yr/hh)</td>
<td>($1,000/yr/hh)</td>
<td>($758/yr/hh)</td>
</tr>
<tr>
<td>Lee</td>
<td>$1,220/yr/hh</td>
<td>$405/yr/hh</td>
<td>$817/yr/hh</td>
<td>$230/yr/hh</td>
</tr>
<tr>
<td></td>
<td>($685/yr/hh)</td>
<td>($199/yr/hh)</td>
<td>($498/yr/hh)</td>
<td>($390/yr/hh)</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>$671/yr/hh</td>
<td>$239/yr/hh</td>
<td>$432/yr/hh</td>
<td>$222/yr/hh</td>
</tr>
<tr>
<td></td>
<td>($406/yr/hh)</td>
<td>($129/yr/hh)</td>
<td>($278/yr/hh)</td>
<td>($121/yr/hh)</td>
</tr>
<tr>
<td>Orange</td>
<td>$542/yr/hh</td>
<td>$219/yr/hh</td>
<td>$322/yr/hh</td>
<td>$225/yr/hh</td>
</tr>
<tr>
<td></td>
<td>($245/yr/hh)</td>
<td>($93/yr/hh)</td>
<td>($153/yr/hh)</td>
<td>($130/yr/hh)</td>
</tr>
<tr>
<td>Duval</td>
<td>$226/yr/hh</td>
<td>$90/yr/hh</td>
<td>$136/yr/hh</td>
<td>$70/yr/hh</td>
</tr>
<tr>
<td></td>
<td>($128/yr/hh)</td>
<td>($44/yr/hh)</td>
<td>($84/yr/hh)</td>
<td>($65/yr/hh)</td>
</tr>
</tbody>
</table>

Note: Means, and standard deviations (in parentheses) across averages for census tracts; $m = \mathcal{M}$ = unmitigated building stock; $m = M$ = mitigated building stock.
Under-estimating the value of mitigation can lead to homeowners making sub-optimal decisions about investing in mitigation measures. To better understand what areas are more likely to be associated with under-estimated EAB values, the correlation was explored between neighborhood characteristics and the magnitude of the underestimate. Specifically, the Pearson correlation coefficient was evaluated between AEAB and several neighborhood characteristics (**Table 5.1-3, Table 5.1-4, and Table 5.1-5**). Using a model that does not consider the implications of texture effects tends to under-estimate the value of mitigation for homes in areas that are more coastal ($\rho = 0.25$); have more exposure to wind-related hazards (strongly correlated, $\rho = 0.57$) (**Table 5.1-3**); have higher prevalence of single-family dwellings ($\rho = 0.33$); and, have lower prevalence of manufactured homes ($\rho = -0.29$) (**Table 5.1-4**). Overall, coastal areas tend to be more exposed to wind-related hazards ($\rho = -0.24$); have lower shielding effects induced by the local terrain ($\rho = -0.14$); and, have higher tunneling effects induced by the local texture ($\rho = 0.27$) (**Table 5.1-5**).

Of the focal counties, Miami-Dade, Lee, and Hillsborough (the southernmost counties) are the most coastal (with decreasing wind exposure and AEAB values). Duval (the northernmost county) is less coastal (and has low wind exposure, leading to much lower AEAB values). And, Orange (relatively more southern) is the least coastal (though has high wind exposure, leading to similar AEAB values as Lee and Hillsborough) (**Table 5.1-3**). Regarding their built environment, all four of the counties have suburban/urban terrain (**Table 5.1-3**); have more than 80% of their households living in single-family dwellings; and, have average replacement cost of roughly a couple hundred thousand.
dollars per household (Table 5.1-4). As they are all densely built-up areas, they are all susceptible to adverse texture effects. However, accounting for these effects scales their EAB values as vastly different rates (as discussed earlier). This difference is driven by growing exposure placing structures at a more critical section of their response spectrum.
Table 5.1-3. Summary of explanatory factors; Locational characteristics.

<table>
<thead>
<tr>
<th></th>
<th>Coastal-ness</th>
<th>Windiness</th>
<th>Terrain</th>
<th>Texture</th>
</tr>
</thead>
<tbody>
<tr>
<td>Florida</td>
<td>-21</td>
<td>41</td>
<td>0.38</td>
<td>1.17 (0.18)</td>
</tr>
<tr>
<td>Miami-Dade</td>
<td>-10</td>
<td>48</td>
<td>0.36</td>
<td>1.24 (0.16)</td>
</tr>
<tr>
<td>Lee</td>
<td>-7</td>
<td>41</td>
<td>0.34</td>
<td>1.12 (0.18)</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>-11</td>
<td>38</td>
<td>0.40</td>
<td>1.16 (0.19)</td>
</tr>
<tr>
<td>Orange</td>
<td>-57</td>
<td>41</td>
<td>0.43</td>
<td>1.21 (0.19)</td>
</tr>
<tr>
<td>Duval</td>
<td>-21</td>
<td>29</td>
<td>0.36</td>
<td>1.14 (0.19)</td>
</tr>
</tbody>
</table>

$\rho$ with EAB ($t = T'$) 0.42 0.71 -0.39 0.28
$\rho$ with EAB ($t = T'$) 0.36 0.70 -0.26 0.57
$\rho$ with AEAB 0.25 0.57 -0.12 0.70

Note: Means, and standard deviations (in parentheses) across census tracts; Pearson correlation coefficients computed statewide from census tract means of EAB, and AEAB; $t = T'$ = 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 (mph); Terrain = census tract surface roughness length (m); Texture = census tract mean of maximum effective wind speed ratio.
<table>
<thead>
<tr>
<th></th>
<th>Single-Family</th>
<th>Manufactured</th>
<th>Multi-Unit</th>
<th>Repl. Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Florida</td>
<td>81%</td>
<td>12%</td>
<td>7%</td>
<td>$208,000/hh</td>
</tr>
<tr>
<td>Miami-Dade</td>
<td>88%</td>
<td>3%</td>
<td>9%</td>
<td>$218,000/hh</td>
</tr>
<tr>
<td>Lee</td>
<td>84%</td>
<td>11%</td>
<td>5%</td>
<td>$246,000/hh</td>
</tr>
<tr>
<td>Hillsborough</td>
<td>78%</td>
<td>13%</td>
<td>9%</td>
<td>$196,000/hh</td>
</tr>
<tr>
<td>Orange</td>
<td>85%</td>
<td>5%</td>
<td>10%</td>
<td>$253,000/hh</td>
</tr>
<tr>
<td>Duval</td>
<td>88%</td>
<td>7%</td>
<td>5%</td>
<td>$246,000/hh</td>
</tr>
</tbody>
</table>

\[
\rho \text{ with EAB (} t = \mathcal{Y} \text{)} = 0.30 \quad -0.35 \quad 0.04 \quad 0.17 \\
\rho \text{ with EAB (} t = T \text{)} = 0.35 \quad -0.35 \quad -0.04 \quad 0.19 \\
\rho \text{ with AEAB} = 0.33 \quad -0.29 \quad -0.09 \quad 0.18
\]

Note: Percentages, and means across census tracts; Pearson correlation coefficients computed statewide from census tract means of EAB, and AEAB; \( t = \mathcal{Y} \) = not considering texture; \( t = T \) = considering texture.
**Table 5.1-5.** Correlation matrix for explanatory factors.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Coastal</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Windi.</td>
<td>0.24</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Terrain</td>
<td>-0.14</td>
<td>-0.27</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Texture</td>
<td>0.27</td>
<td>0.42</td>
<td>0.02</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Singl.-F.</td>
<td>0.14</td>
<td>0.14</td>
<td>-0.16</td>
<td>0.28</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manuf.</td>
<td>-0.23</td>
<td>-0.28</td>
<td>0.17</td>
<td>-0.28</td>
<td>-0.83</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Multi-U.</td>
<td>0.14</td>
<td>0.21</td>
<td>-0.00</td>
<td>-0.03</td>
<td>-0.39</td>
<td>-0.20</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Repl. C.</td>
<td>-0.04</td>
<td>-0.01</td>
<td>-0.07</td>
<td>0.09</td>
<td>0.47</td>
<td>-0.27</td>
<td>-0.39</td>
<td>1</td>
</tr>
</tbody>
</table>

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 (mph); 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.
Lastly, expected losses were computed based on the number of households in each census tract times the mean of expected losses estimated across building footprints that fall within the bounds of that census tract. And, the results show statewide EAB of $8.1 billion per year – this figure includes AEAB of $3.7 billion per year. This implies that conventional loss estimation models may be under-estimating the value of mitigation for Florida by more than 80%. For Miami-Dade, Lee, Hillsborough, Orange, and Duval county, the results show EAB of $2.0 billion, $343 million, $267 million, $176 million, and $56 million per year each – this includes AEAB of $917 million, $111 million, $147 million, $125 million, and $30 million per year.
CHAPTER 6

CONCLUSION

The results of applying the modified framework to a case study on the state of Florida indicate that current loss estimation methods that do not consider texture effects underestimate expected losses (and under-value wind mitigation). Though texture can induce wind loads both higher and lower than conventional estimates, the non-linearity of structural response leads to a 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. For mitigation measures including shutters, straps, and tie downs, the model results yield annualized benefits of $8.1 billion (80% higher than conventional estimates) statewide ranging from $2.0 billion in Miami-Dade County to $56 million in Duval County (respectively, 90% and 100% higher than conventional estimates).

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 not only that such risks have been previously underestimated, but also that 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).
findings strongly suggest that coastal states consider broader efforts to adopt strict building codes – especially in densely built-up areas where risk factors compound.

Moreover, in the scope of this thesis, the benefits of mitigating homes are limited to avoided structural losses. Many other forms of loss accrue to homeowners and communities including the loss of building contents, debris generation, and business interruption (FEMA 2019). Also, mitigating can lead to insurance discounts for homeowners (Malik, Brown, and York 2012). In Southeast Florida, applying the mitigation measures considered in this study on single-family dwellings qualifies homeowners for 83% off wind portions of their insurance premiums (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 imply 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.
APPENDICES

### Table A. Aid to literature review.

<table>
<thead>
<tr>
<th>Main Message</th>
<th>Terrain</th>
<th>Texture</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>In denser (rougher) locales, lower wind loads, lower expected losses.</td>
<td>In dense locales with less disorder (though perfect order not realistic), higher maximum wind loads.</td>
</tr>
</tbody>
</table>

| Theoretical Backing |Terrain effects – Rougher locales 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) (Davenport 1960). | Transition Sublayer (TSL) (where there are recirculation eddies). |

| Applicational Input | Surface roughness length lists (matching descriptions to ranges or characteristic values for roughness length) (typically for homogeneous stretches) (Wieringa 1993; 1992). | Building footprints (required to extract latitudes, longitudes, and footprint areas). |

| Application | Station records – To quantify upwind terrain effects (Wieringa 1993; 1992). 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. |

<p>| Observed Locales | Actual towns and cities (station records) (Shiotani 1962; Steyn 1982; Karlsson 1986; Yersel and 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). |</p>
<table>
<thead>
<tr>
<th>Observed What?</th>
<th>Mean wind speed (wind profile), or mean frictional velocity (station records). Obstruction height, obstruction side-area, and surface area (wind tunnel tests).</th>
<th>Pressure and velocities (at simulated convergence) (read from meshing points) (CFD).</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed Where?</td>
<td>Towers – 20-100 m high, several km in fetch (terrain described qualitatively) (station records). Turntables (wind tunnel tests).</td>
<td>Meshing points on building facades (sample size of 100-300 buildings) (CFD). Reference buildings – 3.5 times density length in radius (RFD).</td>
</tr>
<tr>
<td>Measurements</td>
<td>At least 2 different heights on a single tower, 10s to 100s over months or years (station records). Several repetitions (wind tunnel tests).</td>
<td>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).</td>
</tr>
<tr>
<td>Modeled Quantities</td>
<td>Surface roughness lengths, drag coefficients, or exponents of power law profiles (latter two height-dependent) (Wieringa 1992).</td>
<td>Drag coefficients (from differences of pressures averaged across meshing points on front and back facades).</td>
</tr>
</tbody>
</table>
To characterize local texture, we need to:

- Extract building information
- Compute building-specific drag coefficients

## Extracting building information

We need to:

- Extract latitude, longitude, footprint area
- Assign census tract (by spatial join)
- Export attribute table as .csv
- Convert .csv to .mat

### To extract latitude, longitude, footprint area:

We'll be using:

- Building footprints from Microsoft: [documentation](https://github.com/microsoft/USBuildingFootprints)
- You can find the .geojson files: [here](https://www.dropbox.com/s/u37ke3lrcs7ovn4/Building_footprints.zip?dl=0)

Step 1: Starting QGIS

- Start QGIS

Step 2: Creating .geojson layer

- "Layer" > "Add layer" > "Add vector layer"
- Fill in "Source type": "HTTP(S), cloud, etc."
- Fill in "Protocol": "GeoJSON"
- Fill in "URI": Copy-paste path from File Explorer (e.g., C:\...\Building_footprints\Florida.geojson)
  - "Add" and "close" (might take a moment)

Step 3: Extracting latitude

- "Open field calculator" (abacus icon)
- "Create new field"
- Fill in "Output field name": lat
- Fill in "Output field type": "Decimal number (real)"
- Fill in "Output field length": 10 (default)
- Fill in "Precision": 8
- Fill in "Expression": y($geometry)
- "Okay" (might take a moment)

Step 4: Extracting longitude

- "Open field calculator"
- "Create new field"
- Fill in "Output field name": lon
- Fill in "Output field type": "Decimal number (real)"
- Fill in "Output field length": 10 (default)
- Fill in "Precision": 8
- Fill in "Expression": x($geometry)
- "Okay" (might take a moment)

Step 5: Extracting footprint area

- "Open field calculator"
- "Create new field"
- Fill in "Output field name": area
- Fill in "Output field type": "Decimal number (real)"
- Fill in "Output field length": 10 (default)
- Fill in "Precision": 8
- Fill in "Expression": $area
- "Okay" (might take a moment)

### To assign census tract (by spatial join):

We'll be using:
- Cartographic boundary files from US Census Bureau:
  [documentation](https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html)
- You can find the .shp files:
  [here](https://www.dropbox.com/s/pd6gizwcsvfcivr/Census_tracts.zip?dl=0)

Step 6: Converting .geojson to .csv

- "Layers" (lower LHS) > Right-click on .geojson layer
- "Export" > "Export layer as"
- Fill in "Format": "Comma separated value (CSV)"
- Fill in "File name": Select path from File Explorer (e.g., C:\#92;...\#92;Building_footprints\#92;Florida.csv)
- "Okay" (might take a moment)
- Remove .geojson layer (it's easier to work with delimited layers)
- "Layer" > "Add layer" > "Add delimited text layer" *
- Fill in "File name": Select path from File Explorer *
- Fill in "x field": lon *
- Fill in "y field": lat *
- "Add" and "close" *
- *These steps might be unnecessary.

Step 7: Creating .shp layer

- Look up FIPS code (e.g., for Florida it's 12)
- From File Explorer, drag and drop census tract .shp file

Step 8: Assigning census tract (by spatial join)

- "Vector" > "Data management tools" > "Join attributes by location"
- Fill in "Input layer": Select .csv layer
- Fill in "Join layer": Select .shp layer
- Fill in "Geometric predicate": "Intersects" (default)
- Fill in "Join type": "One-to-one"
- "Run" and "Close" (might take a moment)

### To export attribute table as .csv:

Step 9: Exporting .csv layer

- "Layers" > Right-click on .csv layer
- "Export" > "Export layer as"
- Fill in "Format": "Comma separated value (CSV)"
- Fill in "File name": Select path from File Explorer
- **For ease, use the same naming convention as Microsoft.**
- "Okay" (might take a moment)

### To convert .csv to .mat:

Step 10: Starting MATLAB

- Start MATLAB

Step 11: Converting .csv to .mat

- "Import data"
- Fill in "File name": Select path from File Explorer
- "Open"
- "Import selection" and close window
- "Workspace" (lower LHS) > Right-click on table > "Rename"
- **Call "buildings" to keep generic.**
- "Workspace" > Right-click on table > "Save as"
- Fill in "File name": Select path from File Explorer
- **For ease, use the same naming convention as Microsoft.**
- Fill in "Save type as": "MAT-files (*.mat)"
- "Save"

## Computing building-specific drag coefficients

Step 12: Navigating to correct working directory

- Download code: "city_texture_cd_model.mat", "run.mat", "index.m"
- From "Current folder" (upper LHS), copy-past your .mat files to the folder with "city_texture_cd_model.mat"

Step 13: Running the code

- In "Command window" (bottom of page), run "index.m"

Step 14: Sharing the results

- **You'll have one .mat and one .csv file for drag coefficients in each state.**
- Upload to Dropbox :)

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# To discuss the economic implications of texture, we need to:

- Collect necessary information
- Compute building-specific expected annual losses (EAL)

## Collecting necessary information

In one folder collect:

- Your .mat files from last week
- Files in Hazus/Hazus_mat
- Files in ACS_DP03/ACS_DP03_mat
- Files in ACS_DP04/ACS_DP04_mat
- Files in PUMS/PUMS_mat
- Files in Census_tracts_neighbors/mat
- Entire code under Week_3

## Computing building-specific expected annual losses (EAL)

Step 1: Running the code

- In "Command window" (bottom of page), run "index.m"

Step 2: Sharing the results

- **You'll have 6 .mat and 6 .csv files for EALs in each state.**
- **2 of each are 'EAL' (in $1000 per household).**
- **2 are 'EAL_PerValue' (normalized by home value).**
- **2 are 'EAL_PerInc' (normalized by household income).**
- **Each includes 'Case0' (for an unmitigated building stock) and 'Case1' (for a mitigated building stock).**
- **Also, each includes 'Hazus' (based on a framework developed by FEMA) and 'New' (based on an updated framework).**
- Upload to Dropbox :)
Additional reading on Hazus:

- On its terrain and wind modeling: [this](https://ascelibrary.org/doi/full/10.1061/%28ASCE%291527-6988%282006%297%3A2%2882%29)
- On its loss modeling: [this](https://ascelibrary.org/doi/full/10.1061/%28ASCE%291527-6988%282006%297%3A2%2894%29)
REFERENCES


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https://doi.org/10.1016/S0167-6105(98)00136-6.


U.S. Census Bureau. n.d. “Census Tracts.”


Vickery, Peter J., Jason Lin, Peter F. Skerlj, Lawrence A. Twisdale, and Kevin Huang.


