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A Framework for Assessing Facility-Level Vulnerability and Risk to Extreme Weather Events

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THESIS

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Abstract

Intensifying extreme weather events, tied to the rise in the global average temperature, put global built infrastructure at risk. This presents a daunting challenge for organizational leaders who are tasked to determine how best to adapt current infrastructure to uncertain future events. To develop adaptation plans and policies, vulnerability and risk must be downscaled to an actionable scale, such that planners, designers, and engineers can make adaptation recommendations. However, previous research has largely assessed risk at coarser scales, e.g., regional, national, or global. These assessments are informative, but do not help those tasked to lead adaptation to make detailed, actionable plans. This research focuses on the production of a methodological framework for downscaling extreme event threats to calculate vulnerability and risk at the facility. Using Tyndall Air Force Base (TAFB) as a case study, a building envelope and profile fragility curve-based framework is proposed and tested that uses existing facility attributes to calculate vulnerability to hurricane-force winds. Vulnerabilities are translated to risk using historical return periods for Saffir-Simpson-scale hurricanes. Outputs for Tyndall AFB suggest that risk is highest for Category 2 and 3 storms, and that relative facility vulnerability rankings are stable for Category 3 and larger storms. Generally, this framework provides planners, designers, engineers, and decision makers with the information necessary to determine the extreme-event risk for their facilities such that they may prioritize adaptations, wholistically assess campus-level risk, and determine design events.

To my wife and children - There are no words meaningful enough to capture the appreciation I have for each of you and the sacrifices you have made. Your love and never ending support in all of my endeavors are unwavering.

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First, I would like to thank my wife, without your patience and understanding over the past year, none of this would have been possible. You are my foundation and inspiration to be my best in all aspects of life.

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I. Introduction

1.1 Background

Over the past century, average global temperatures have risen by 1.8°F (1°C) (USGCRP 2018), and the effect on the environment from this increase, and projected increases, holds the potential to intensify damaging extreme weather events (Smith & Katz 2013; Smith & Matthews 2015). Compounding extreme event intensity and frequency changes, are increases in the exposure and vulnerability of communities, which are a result of population and associated infrastructure development (USGCRP, 2018). There are calls for hard and soft adaptations, particularly for coastal communities that face seasonal threats from tropical storms. However, vulnerability and risk projections are mostly limited to unactionable spatial scales (Gade et al. 2020).

Coastal Department of Defense (DoD) installations are inseparable from the communities they support, and both affected by the same extreme events. Since 2017, affected DoD installations estimated 13 billion dollars in damages, the vast majority of which is tied to tropical storms (DoD, 2022). In addition to the economic impacts felt by coastal installations and communities, degradation of defense critical infrastructure puts mission at risk and can reduce power projection potential for significant amounts of time.

In 2021, Executive Order 14008 put climate change centerstage and called on defense leader to address climate change risk in future development plans, produce analyses that aimed at identifying climate-induced security implications. However,

Executive Order 14008 is one of many mandates the DoD has been given to identify the implications of a changing climate. Since 2010, the DoD has recognized climate change as a threat, and has incorporated climate-informed decision-making in the implications of policies, directives, and plans towards operations, mission, and facilities. Leading up to 2019, the DoD published a total of 20 reports, directives, and instructions related to the climate change related impacts (OUSD A&S, 2021). However, the outcomes of these initial attempts are mostly limited in scope, lacked practical guidance for installations looking to adapt, and therefore had little impact. In context of built infrastructure, the most significant contributors to the DoD's lack of significant action was identified as a shortage of *expertise* required to 1) identify and downscale climate projections and future extreme weather threats to the facility and infrastructure level; 2) translate threats to exposure, vulnerability, and risk; and 3) develop practical adaption pathways from risk profiles (GAO 2019). Engineers and planners can produce climate-minded designs, but without understanding facility-level vulnerability and risk—which they are not equipped to calculate—facility and infrastructure adaptation cannot occur.

In an effort to amend shortfalls identified by the Government Accountability Office, the DoD continued its efforts through the creation of the Defense Climate Assessment Tool (DCAT), and the DoD Regional Sea Level (DRSL) database. These tools deliver high-level assessments of vulnerability to climate related events. These programs are meant to aid in long-term planning and informed decision making, but admittedly lack "tactical" spatial granularity required to enable installation-level action.

1.2 Problem Statement

The paucity of effort towards developing tools that link the science of climate change-driven extreme events to the practitioner must be addressed to provide stability for coastal communities and DoD installations. Decisions to adapt infrastructure to impending extreme events will be costly, and because of this there is a need for prioritizing adaptation decision making. For the DoD, this means identifying and adapting facilities that present the largest risk to mission failure, and from an installation-level aggregating installation risk and determining design events. The tools that are available to installations do not address these issues.

1.3 Research Objectives

This thesis addresses the lack of tactical-level assessment with a novel, facility level, fragility curve-based vulnerability and risk assessment tool, which downscales susceptibility to actionable resolution in order to plan, prepare, and adapt to extreme weather events. To accomplish this, the focus of this thesis is on the following objectives:

1. Determine and consolidate relevant facility data, to characterize the attributes of facilities that contribute to exposure and vulnerability, e.g., condition, economic value, and mission importance.
2. Identify and adapt quantitative vulnerability and risk assessment methods that leverage facility data identified in (1).

3. Produce communication and visualization tools that target providing planners, engineers, and decision makers with information that enables prioritization of adaptation actions and mission risk.

II. Literature Review

2.1 Chapter Overview

This chapter discusses research relevant to the assessment of facility vulnerability and risk emanating from intensified extreme weather events. First, definitions and accepted practices of quantifying facility vulnerability, tied specifically to extreme events are discussed. Second, the process for developing DoD infrastructure and facilities within the Air Force Comprehensive Assessment Management Plan (AFCAMP) is reviewed and assessed to determine the use of current decision components and explore opportunities to allow infrastructure adaptation to extreme events.

2.2 Assessing Vulnerability and Risk

Climate change risk and vulnerability management approaches exist across a number of spatial scales: national, state or county/city levels. Beginning in 1990, the Intergovernmental Panel on Climate Change (IPCC) has contributed to evaluations of climate change impacts, adaption, and vulnerability. As early as 1997, it defined vulnerability as a concept penetrating the human-natural interfaces of climate (Watson, 1997). The IPCC's definition of vulnerability—a function of exposure, sensitivity, and adaptive capability—is implemented by many focused on climate-related vulnerability research (Watson, 2001). The three vulnerability dimensions are characterized as 1) exposure, which describes the stressors and entities under stress, 2) sensitivity, which describes the direct impacts of the stresses; and 3) adaptive capacity, which describes the

system's ability to cope, adapt, or recover from those effects (Figure 1) (Polsky et al., 2007). Risk is characterized as the potential consequences for a system that is represented as a function of two elements defined as 1) the likelihood of an event occurring (e.g., wildfire, drought, hurricane, etc.) and 2) the consequences of such an event taking place (Cardona et al., 2012).

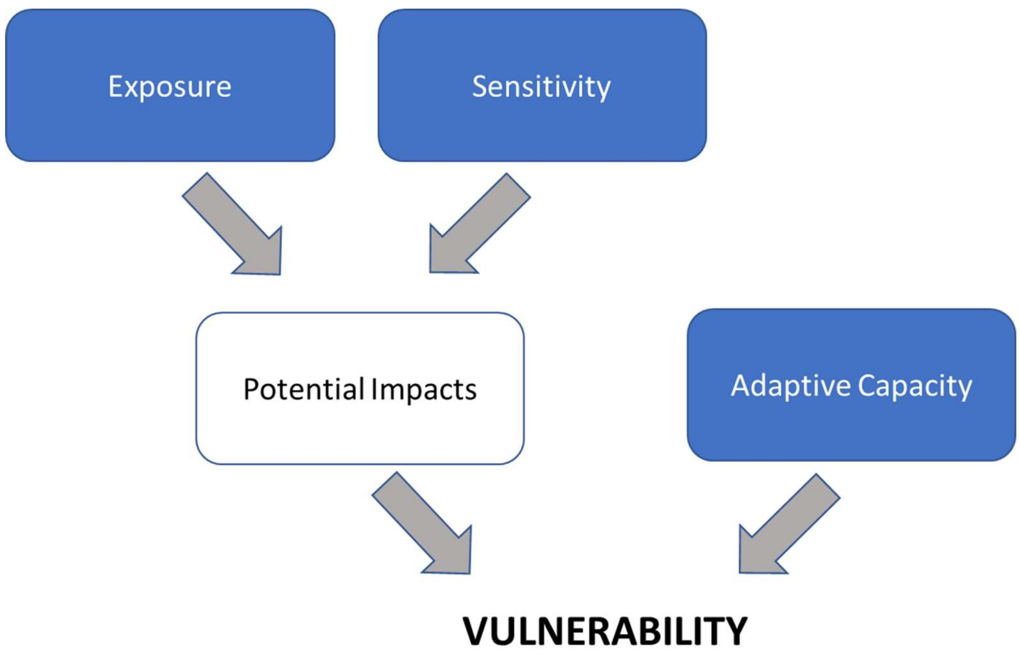


Figure 1. Vulnerability assessment framework as defined by the IPCC

The concept of measuring vulnerability and risk to a system has been applied across a broad spectrum within the realm of climate and human systems, such as regions impacted by tropical cyclones (Nayak et al. 2014; Nazir 2015), midwestern farming affected by winter storms (Zhang et al 2021), and areas impacted by flooding (Hinkel et al 2009; Kim et al. 2011). The first step in quantitative vulnerability and risk assessment

for assets is to establish an attribute library for assets of interest, based on the elements of an assets construction and value that are of interest to the decision maker (Abokwitz et al. 2017). Next the exposure sensitivity of asset attributes is explored using common quantitative methods, e.g, Principal Component Analysis (PCA); or qualitative methods, e.g., survey interviews to industry experts (Zhang and Liang 2021). Finally, a calculation of vulnerability and risk is made. For vulnerability, the equation can be represented in multiple ways and combinations of exposure, sensitivity, and adaptive capacity, which can be weighted and either additive or multiplicative. Risk is calculated simply the product of the vulnerability and spatial and/or temporal likelihood of event occurrence.

Many vulnerability and risk using multiple framework include inputs measured on different scales, which is resolved through rescaling using linear and nonlinear normalization techniques (Elizabeth et al 2010; Kim et al. 2011; Brooks et al. 2015; Abkowtiz et al. 2017), the most common of which a are min-max and z-score (Wu et al. 2014; Zhang et al. 2021). Applying concepts of vulnerability and risk at the facility-level enables installation and enterprise decision makers and planners to scale the measured exposure levels of extreme weather events down to actionable level for adaption decision making.

2.3 Air Force Comprehensive Asset Management Plan

Any facility-level vulnerability and risk model intended to inform adaptation decision making ought to be constructed to operate within the constraints of the project funding system that allocates capital to facilities projects. The Department of Defense,

not unlike any firm that operates campuses, has traditionally used infrastructure criteria to prioritize maintenance, renovation, and construction spending. The Plant Replacement Value (PRV), Mission Dependency Index (MDI), and Condition Index (CI) ratings connected to infrastructures and facilities, and are commonly used by the Air Force, and other services, to assess which infrastructure projects are worth financing each fiscal year. The Air Force Comprehensive Asset Management Program (AFCAMP) presently employs a technical project scoring methodology, based on existing asset Probability of Failure (PoF) and Consequence of Failure (CoF) values (AFCEC 2020). CoF of an asset is determined by its MDI, and PoF is determined by the CI. MDI is a measure of facility connectedness to mission (0-100), and CI is a measure of facility condition (0-100). Assets that are more critical to mission—have a higher MDI value—and are in poor, but repairable condition—have a lower CI—are more likely to get a higher technical project score and receive funding in the AFCAMP process. However, this approach to funding facility projects ignores vulnerability or risk to failure from disruptive occurrences like extreme weather events.

In addition to the scoring process outlined above, the AF also recognizes that not all assessments should be mission dependency and condition-based. The use of Non-Condition Based (NCB) assessments are used to augment the AFCAMP scoring model, to tip the balance toward specific military objectives, e.g., unmanned aerial systems, climate-resilience or -robustness, etc. Examples of NCBs include Specific Enterprise Execution Direction (SEED), Enterprise Objective (EO) categories, and General

Categories (not captured by SEEDs or EOs) (AFCEC 2020). SEEDs are aimed at a specific installation and intend to reward projects that support a new mission set or requirement. EOs are similar to SEEDs, but they are not tied to a specific base, but rather target AF-wide strategic master plans. EOs are classified into any of following seven categories: 1) mission resiliency in contested environment, 2) nuclear enterprise sustainment and modernization, 3) right-size mission footprint supporting mission and partners, 4) mitigate risk to mission essential functions, 5) mission assurance and redundancy features, 6) lifecycle reduction through partnership, or 7) restore military readiness and while building a more lethal force. Clearly, climate resilience and robustness-centered work could be tied to a SEED, e.g., adding robustness to no-fail missions at a coastal installation; and EOs, mainly through categories 3-6.

2.4 Summary

This literature reviewed discussed relevant research related to assessing vulnerability and risk in the context of extreme events and built infrastructure. Explored were the underlying definitions of vulnerability and risk, and the components of each that are downscaled to the facility level. Then the review explored the current process for funding projections within the AF through assessing the AFCAMP business rules. There exists a disconnect between policies and directives that are driving climate-change adaption signals, the appropriate downscaling of risk to actionable levels, and the policy lever required to incentivize development of projects that support adaptation mandates.

The remainder of this research addresses the downscaling of risk, using Tyndall AFB as a case study.

III. Case Study: Tyndall AFB

3.1 Tyndall AFB

Tyndall Air Force Base (TAFB) is a United Stated States Air Force (USAF) installation located 12 miles east of Panama City, on Florida's Gulf Coast (Figure 2). The base occupies 14.5 squares miles, has a total resident population estimate of 2,779 according to the United States Census Bureau (USCB), with many more employees commuting each day. There are approximately 5.6 million square feet of facilities, 62 miles of paved road, 600,000 feet of electrical lines, and roughly 1.2 million feet of sewer, water, and storm water lines. The base is home to the F-22 Raptor, is in the process of bedding down an F-35 Lightning mission, and serves as a main focal point executing the USAF's training for air combat operation. Not unlike all coastal communities in Florida and along the Gulf, Tyndall AFB is susceptible to the impacts of climate change, mostly borne through sea-level rise, intensified precipitation events, and most acutely through hurricanes. On October 10, 2018, Hurricane Michael, listed as a Category 5 Hurricane on the Simpson-Saffir scale, made landfall directly over Tyndall AFB Tyndall AFB, and produced an estimated $3 billion in total damage; more than 50% of the facilities on the installation needed "extensive" repair, or complete reconstruction (Beven et al. 2019; Everstine, 2019). TAFB's geographical location and importance to the USAF presents a unique challenge for planners, who must determine potential adaptation strategies that could minimize impact of future intensified weather events. Using TAFB as a case study, facility-level vulnerability and risk will be assessed

against hurricane wind-driven scenarios using existing facility attributes. The analysis aims to demonstrate how to link existing facility data with extreme weather damages in order to assess those areas and facilities that are most impacted in order to give leaders an idea of where to focus time, money, and personnel in mitigation efforts.

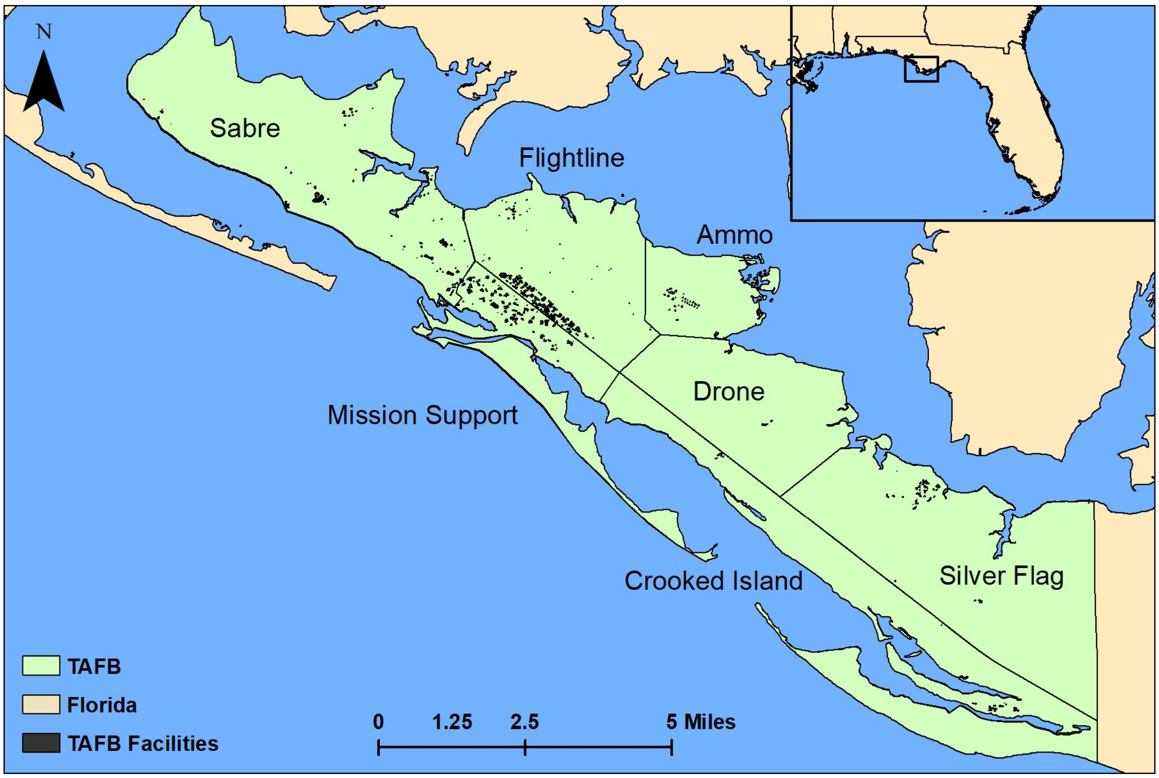


Figure 2. Regional overview of TAFB and geographically-defined mission districts.

IV. Data

4.1 Data Overview

The analysis performed in this research relies on established USAF facility databases, Real Property (RP) and BUILDER, and leverage damage state (fragility) curves drawn from Federal Emergency Management Administration's (FEMA) Hazard modeling software (HAZUS) to produce facility-level vulnerability assessments. Vulnerabilities are translated to risk using likely return periods of wind speeds tied to the Saffir-Simpson hurricane scale. This section details the data used in the analysis, how each are obtained, merging of the RP and BUILDER databased, and the FEMA HAZUS damage state curves.

4.2 Vulnerability/Risk Analysis Database

The variables required for the vulnerability and risk analysis are those that represent economic value, mission importance, and overall condition. Additionally, latitude and longitudinal coordinates of each facility are needed to map results spatially. Lastly, and most importantly, physical facility attributes, e.g., envelope material, facility height, etc., are required to link each facility to FEMA fragility curves. All required data are consolidated in a new database (Table 1).

Table 1. Vulnerability/Risk Analysis Data Base. For BUILDER, “Final-*n*” refers to a specific sheet within the BUILDER database. RP is further discussed in 4.2.1 and BUILDER in 4.2.2.

Variable	Description	Source Database	Use
Building Number	Unique identifier for each facility	RP/BUILDER	Links RP and BUILDER
Latitude/Longitude	Geospatial coordinates	RP	Mapping of vulnerability/risk
SDS Feature	Name of facility (General Description)		
Year Built (Age)	Year of completed construction	BUILDER – Final 01	Determination of Age-Assessment of Vulnerability/Risk
PRV	Cost of replacing the facility with present day cost		Assessment of Vulnerability/Risk Assessment of
MDI	Metric used to determine the relative criticality of infrastructure assets; scale: 40 to 100		
BCI	Performance-based metric for overall building condition; scale: 0 to 100		
Floors	Number of faculty stories		Determination of HAZUS facility type/fragility curve
Component (B2010)	Facility system detail, e.g., floor construction, roof construction, exterior walls, etc.	BUILDER – Final 05	Determination of HAZUS facility type
Material/Equipment Category (B2010001)	Facility system components e.g., exterior closure, windows, water closets, etc.		Determination of HAZUS facility type

Component Subtype	Facility system components material/equipment category e.g., asphalt shingles, metal panel, concrete block, etc.		Determination of HAZUS facility type

Plant Replacement Value (PRV) is the current replacement value of the facility; Mission Dependency Index (MDI) is a measure of facility connectedness with installation mission, Building Condition Index (BCI) is the current physical condition of the facility. PRV is a function of age and condition, though each is not highly correlated with any other given the complexity of facilities, and the inconsistent rate of component degradation, e.g., roof, envelope, etc. MDI is a metric used within the AF to determine the relative criticality of infrastructure concerning organizational missions. It applies risk management concepts of replicability and interruptability to develop a score ranging from 40 to 100 that illustrates the AF's mission dependency on individual facilities (Depalmer et al. 2021). BCI is a performance-based building metric that demonstrates a facility's condition as a function of its many systems (Uzarski et al., 2019). Using a weighted average technique, individual component indices are aggregated to a to a building level. This weighting is usually based on the replacement value of the individual components, with higher-cost items receiving a larger weight in the overall BCI score, but also based on criticality or risk concerns. In relation to the vulnerability framework the factors Age, BCI, MDI, and PRV are related to the sensitivity component as they help characterize the severity of the impact to the exposure of hurricane wind speeds. The data used here

constitutes a best-guess as to features that contribute to vulnerability and risk at the facility-level. The framework discussed below could easily be expanded to account for additional parameters or reformulated completely to suit any firm's needs.

4.2.1 Real Property

Within the DoD, Real Property (RP) is defined as land and anything permanently affixed to it, such as buildings, their installed systems, building equipment, and can include roads, parking facilities, fences, utility systems, and structures (Watson, 2016). RP data for this research is obtained from the TAFB Real Property Accountability (RPA) office, which was last updated July 2018. Future updates are expected when Hurricane Michael-related demolition, facility renovation, and construction are completed. From the RP file, the only data of interest is a facility's building number, latitude and longitude coordinates, and name of the facility. The RP file contains all facilities located at Tyndall Air Force Base (TAFB). Removing unsuitable facilities from the RP file was necessary due to missing data. First, all housing facilities, detailed as duplexes or single-family homes, are removed from the RP data set. The removal of housing facilities from the analysis is partly done because the vast majority of housing units on base do not have MDI values. Additionally, any BCI values for these facilities are unreliable, as condition assessments are not generally completed for homes. This is because the DoD has privatized most of its housing developments (NDAA, 1996). All maintenance and building assessments are completed by a private company, and there is no well-defined

process for tracking condition assessments in BUILDER. After housing units, any duplicate entries found within the RP data are removed.

4.2.2 BUILDER

In addition to the RP data, the analysis also relies on data from BUILDER, a web-based Sustainment Management System (SMS) application developed by the U.S. Army Engineer Research and Development Center (ERDC) Construction Engineering Research Laboratory (CERL). In 2013, DoD leaders implemented BUILDER as the standard for all asset management in the DoD (Kendall, 2013). The purpose of this application is to help civil engineers, technicians, and managers decide when, where, and how to maintain the best individual buildings, as well as their associated systems and components (ERDC 2012). BUILDER contains standard reports that provide users with essential and frequently requested outputs for asset management. In addition to the usual information, BUILDER also can create custom reports. In 2019 the ERDC/CERL, in conjunction with the Air Force Civil Engineering Center (AFCEC), released a list of custom reports for specific use within the department of the USAF.

The two reports of interest are the Final 05 – Inspection Summary Report (Final 05) and the Final 01 – Building Summary Report (Final 01). The Final 01 report consists of 18 variables identifying building-level information related to each facility. In contrast, the Final 05 report contains 20 variables identifying various asset management information associated with a facility distilled down to each of its components. Each of

the variables captured from these reports serve two purposes to 1) link the newly created database to FEMA HAZUS fragility curves; and 2) quantify vulnerability and risk.

4.5 Linking of RP and BUILDER, and Facility Screening Procedures

To create the database required to calculate vulnerability and risk, the data obtained from RP and BUILDER was merged. Combining the databases is accomplished by utilizing the building number of the facility, which was the common linkage between the two. The initial count of the facilities was 1,232. After the removal of the data as discussed above, e.g., housing (n = 692) and duplicates/non-vertical facilities (n = 44), the final count of facilities included in this study is obtained (n = 492).

Within the newly created database, there are instances of incomplete data for variables associated with Age, BCI, MDI, and PRV, for facilities that are otherwise fully parameterized. Missing values associated with these variables are replaced with a Weibull-based distribution model. That is, a Weibull distribution is fit to each variable's data, and for facilities with missing data in a particular data category, a value is randomly drawn with replacement. The decision to use the Weibull distribution is due to its versatility in analyzing small sample sizes and mimicking other distributions (Betz et al. 2021; Brown et al. 2021; Grussing et al. 2012). Table 2 shows the number of missing facility-attributes and the associated Weibull distribution parameters, and Table 3 shows a summary of complete facility data within each of TAFB's districts (Fig. 1) used to determine facility vulnerability and risk profile.

Table 2. Weibull distribution parameters for missing values

Variable	Facilities with Missing Data	Scale	Shape
Age (yrs)	19	44.998	2.092
BCI	63	84.341	10.084
PRV ($)	20	1,846,062.4	0.595
MDI	21	71.927	5.935

Table 3. Facility attribute breakdown by TAFB mission districts

District	μAGE	μPRV ($ Mill)	μMDI	μBCI	Facility Count
Ammo	38	$0.993	68	81	37
Crooked Island	42	$1.651	74	74	32
Drone	36	$1.802	72	80	6
Flightline	43	$3.588	69	78	149
Mission Support	43	$4.578	64	82	114
Sabre	45	$2.190	60	83	98
Silver Flag	19	$1.109	67	79	56

No one district is particularly more or less distinguishable from any other, other than facility count. The range of each attribute is relatively low except for that of Age and PRV. Districts such as Mission Support and Flightline contain a larger volume of facilities, which ultimately gives these districts a higher spatial probability of being impacted, in terms of total PRV exposed, due to the high degree of stability in wind fields created by hurricanes, i.e., Tyndall is likely too small to see significant difference in wind speeds across the installation.

Of great importance in multivariate models is independence between variables. Multicollinearity, or a correlation between input variables has the potential to bias model outputs, and as such the correlation between each variable must be computed (Table 4). Overall correlation values presented in the table show weak or non-existent relationships The lack of multi-collinearity between the variables demonstrates that no combination of variables that have the potential to bias the model due to multicollinearity, and bias reduction techniques like principal component analysis are not required.

Table 4. Correlation analysis for facility attributes (*n* = 492)

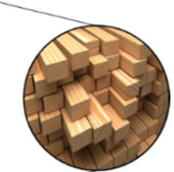
	Age	PRV	MDI	BCI
Age				
PRV	0.0220			
MDI	-0.0596	0.1003		
BCI	-0.1302	0.0294	-0.0251	

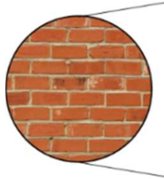
4.6 HAZUS-MH Facility Type Fragility Curves

Fragility curves, which describe the relationship cumulative probabilistic damage expectations and wind speed, are used to estimate wind-driven facility damage. The curves are developed by FEMA and obtained from HAZUS. To effectively model the damage output for the facilities at TAFB, each must be classified into a facility type consistent with those that appear in HAZUS. That is, the diversity of facility construction types available for this analysis is categorically limited to the number available in HAZUS. The HAZUS program contains 39 specific building types (SBT) that separated

into five specific building classifications (SBC): wood, masonry, concrete, steel, and manufactured homes. Figure 3 provides an example of the facility classifications within HAZUS; a complete list of all 39 SBT can be found in Appendix A.

HAZUS - MH Facility Breakdown Example		
SBC	SBT	Description
WOOD	WSF1	Wood, Single Family, One Story
WOOD	WSF2	Wood, Single Family, Two or More Stories
WOOD	WMUH1	Wood, Multi-Unit Housing, One Story
WOOD	WMUH2	Wood, Multi-Unit Housing, Two Stories
WOOD	WMUH3	Wood, Multi-Unit Housing, Three or More Stories
MASONRY	MSF1	Masonry, Single Family, One Story
MASONRY	MSF2	Masonry, Single Family, Two or More Stories
MASONRY	MMUH1	Masonry, Multi-Unit Housing, One Story
MASONRY	MMUH2	Masonry, Multi-Unit Housing, Two Stories
MASONRY	MMUH3	Masonry, Multi-Unit Housing, Three or More Stories





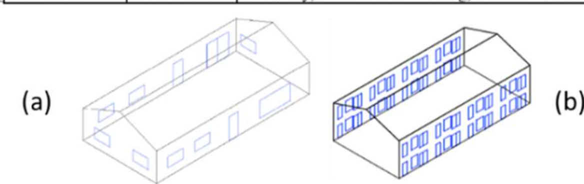


Figure 3. Breakdown of HAZUS-MH facility classification for single and multilevel wood and masonry residential structures (a) modeled single family house one story, (b) modeled multi-unit housing two story.

Determining the HAZUS facility-type corollary for each of TAFB's facilities is done by using data from both RP and BUILDER. As mentioned previously, the Final 05 report data is filtered to Component B2010 – Exterior Walls and Material/Equipment Category B2010001 – Exterior Closure. This type of information provides an identifier for each facility's structural makeup and is the link between facility data and FEMA

HAZUS fragility curves. Using the facility's Component Subtype, a judgement-based determination is made into which SBC a facility would categorize into. For example, if a facility's Component Subtype is described as *adobe*, for which a fragility curve does not exist, the facility SBC would be identified as *masonry*. The Final 05 report had sufficient information to determine the SBC for 400 of 492 facilities (5% Concrete, 65% Masonry, 26% Steel, and 3% Wood). For the remaining 92 facilities that were not able to be matched to a HAZUS facility type, the proportion of the SBC-type from the 400 facilities was followed to assign facility types to the remaining 95 facilities, e.g. 5% of the 92 facilities were categorized as 'concrete'. The final distribution of SBC for each TAFB facility can be seen in Table 5.

Table 5. TAFB facility SBC distribution

SBC	Added (n = 92)	Total (n = 492)	Percent Total
Concrete	5	27	5%
Masonry	58	320	65%
Steel	26	131	26%
Wood	3	14	3%

After determining each facility's SBC, variables Floors (Final 01) and SDS Feature (RP) are used to assign each facility at TAFB with an SBT. Floors are the equivalent of number of stories within a facility, and SDS Feature describes the use of the facility e.g., residential, commercial, etc. In total, there are 11 different SBTs that are used to construct the facility profile at TAFB (Table 6). These SBT are used to determine the sets of fragility curves that are matched to each facility.

Table 6. TAFB facility SBT distribution

SBT	Total	Description
CECBL	27	Concrete Engineered Commercial Building, Low-Rise
MECBL	262	Masonry Engineered Commercial Building, Low-Rise
MECBM	2	Masonry Engineered Commercial Building, Mid-Rise
MERBL	7	Masonry Engineered Residential Building, Low-Rise
MERBM	9	Masonry Engineered Residential Building, Mid-Rise
MMUH1	34	Masonry, Multi-Unit Housing, One Story
MMUH2	6	Masonry, Multi-Unit Housing, Two Story
SECBL	119	Steel Engineered Commercial Building
SPMBL	6	Steel Pre-Engineered Metal Building, Large
SPMBM	6	Steel Pre-Engineered Metal Building, Medium
WSF1	14	Wooden Single Family, One Story

The district-level SBC abundance (Fig. 4) provides a lens through which to view potential vulnerability. That is, concrete and masonry facilities are generally believed to withstand greater hurricane winds than wood and other building materials, and as such, districts with a higher percentage of concrete and masonry, e.g., mission support, may exhibit lower vulnerability. SBC masonry appears more often than all others and is the most frequent type within the Mission Support, Flightline, and Sabre districts. Steel is

the second most common SBC, primarily located in the Flightline, Silver Flag, and Crooked Island districts.

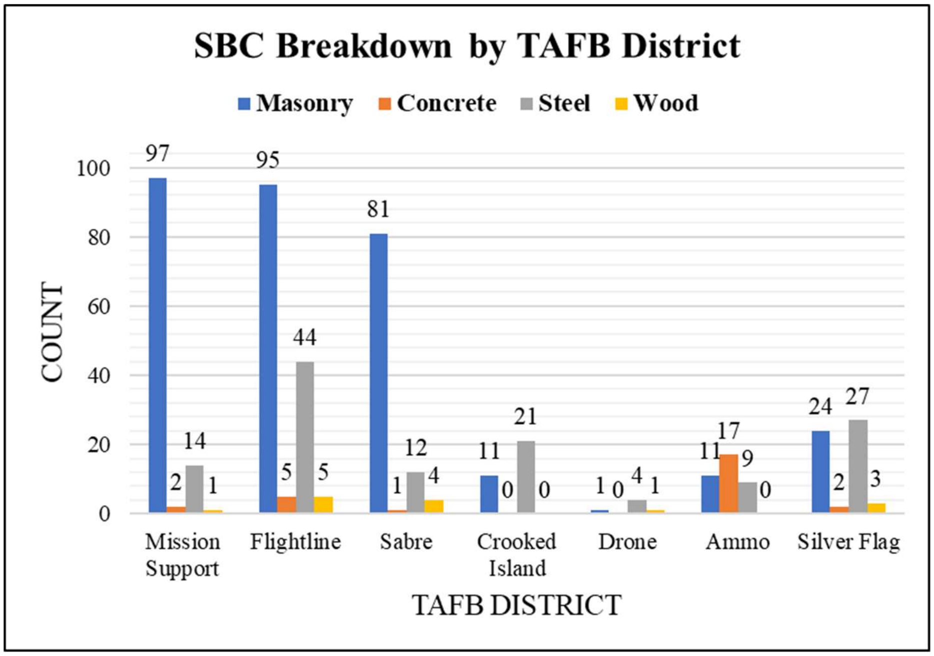


Figure 4. Facility SBC distribution by district.

4.7 Hurricane Return Period and Risk

Existing research establishes recurrence intervals for each categorical hurricane as defined by the Saffir-Simpson scale, for the state of Florida (Parisi et al., 2008) (Table 7). The product of annual storm probability and facility vulnerability is risk. The risk assessment provided in this work essentially prorates vulnerability, by accounting for the fact that storms with longer return periods, while likely to increase facility and portfolio vulnerability, may actually present a lower risk to the facility.

Table 7. Hurricane recurrence intervals 1900-2006 for Florida U.S. (Parisi et. al, 2008)

Saffir-Simpson Category	Return Period	Annual Probability
1	1.7	58.82%
2	2.4	41.67%
3	3.3	30.30%
4	6.5	15.38%
5	23.4	4.27%

V. Methodology

5.1 Methodology Overview

The objective of this thesis is the development of a framework for facility-level identification of vulnerability and risk, in order to help leaders plan, prepare, and adapt for intensified natural threats. It requires a technical approach, which links essential attributes of the facility to the hazard such that vulnerability and risk can be calculated. The framework presented in this section relies on fragility curves, tied to existing facility data, which are derived from FEMA HAZUS Hurricane Model TM 2.1 (2017). The following chapter details taking the obtained and developing a methodological process for accomplishing the research objective (Figure 5). First, fragility curves are assigned to each facility to estimate wind-driven facility damage, for which an Expected Damage Output (EDO) metric is produced (5.2). Then, formulation of vulnerability is introduced (5.3) followed by risk (5.4). Lastly, the process of taking vulnerability/risk and mapping within GIS is discussed.

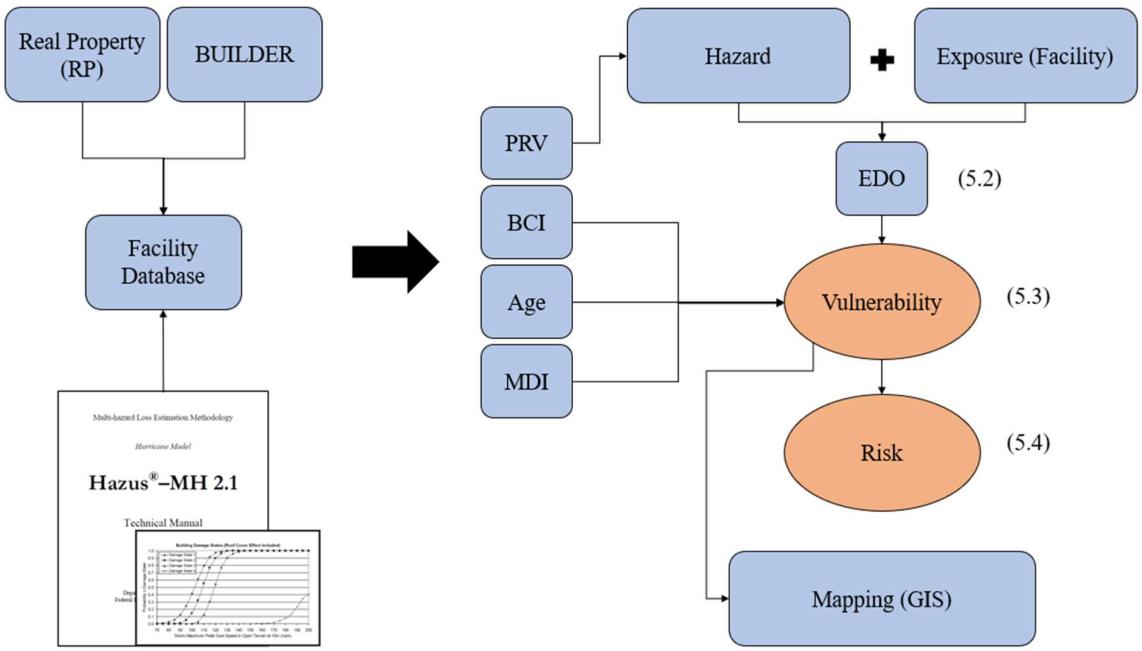


Figure 5. Methodological approach for assessing facility level vulnerability and risk.

5.2 Expected Damage Output (EDO)

A primary component of facility vulnerability and risk analysis involves calculating the physical damage it might sustain under wind loading. In the context of this research, the Expected Damage Output (EDO) is developed as a vulnerability metric, which estimates physical damage. The EDO is a novel implementation of quantitative vulnerability analysis, as it utilizes existing data to link defined FEMA fragility curves employed within HAZUS to a facility.

5.2.1 Fragility Curve Calibration

Fragility curves define the probability that a facility reaches or exceeds a specific damage state under a given perturbation (Mohamed, 2018). In risk assessment, the

primary use of fragility curves is employed to estimate damage and loss for a given facility during a seismic event such as an earthquake (Hariri et al., 2016; Nielson et al. 2012; Shinozuka et al. 2000). In addition to seismic events, wind-induced loads, like those witnessed with hurricanes, can also be represented employing fragility curves. As mentioned previously, HAZUS-MH produces risk assessments for a specified wind-induced event. In HAZUS-MH, a physical damage model, compares wind loads to resistance values for various components from wind-induced inward and outward pressures on facility components, such as roof cladding, windows, roof cover, roof deck, joint failures, and walls (Vicerky et al. 2006). The damage states have been developed using a 20,000-year simulation of hurricanes by performing 30 simulations of each storm (FEMA 2017). The modeled results produce statistical outputs used to develop damage state fragility curves ranging from 0 (no damage) to 4 (destructive) for each SBT. Figure 6 depicts the damage state curves for SBT MECBL found in the FEMA HAZUS Hurricane-Model Technical-Manual (TM) 2.1.

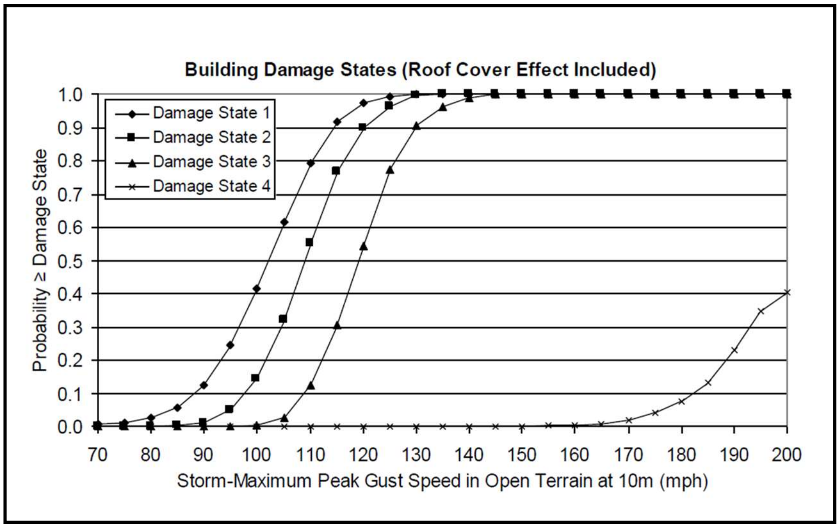


Figure 6. Damage State vs. Peak Gust Wind Speed – Two Story Engineered Commercial Building; from FEMA HAZUS Hurricane Model TM 2.1 (2017).

It is important to note that HAZUS does not provide the functional forms and parameter values for its fragility curves directly, and thus they must be determined for curves to be recreated. By inspection, the coordinates along the curve are determined, and used as inputs to a software-drive logistic-fit model to produce the continuous equations required to simulate damage states for any wind speed. The damage state curves for each SBT in HAZUS-MH are Sigmoidal, and are best fit by a logistic function (Equation 1):

$$Q(t) = \frac{Q_{inf}}{1-e^{-\alpha(t-t_{hal}\ )}} \tag{1}$$

where Q_{inf} is the curves maximum value; α is the logistic growth rate or steepness of the curve*;* and *t*/t_{half} is the value of the sigmoid's midpoint. The function inputs are *t* and *Q*, where *t* represents the storm-maximum peak wind gust speeds in 10 mph increments,

starting at 80 mph and ending at 200 mph; and *Q* represents the probability of reaching or exceeding a specific damage state, given variable *t*. Using SBT MECBL as an example, Table 8 shows the parameters of *Q* and *t*.

Table 8. Damage state modeling inputs for SBT MECBL

t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.02	0.001	0	0	
90	0.12	0.002	0	0	
100	0.41	0.15	0.001	0	
110	0.89	0.56	0.12	0	
120	0.98	0.9	0.55	0	
130	0.99	0.99	0.9	0	
140	0.99	0.99	0.99	0	
150	0.99	0.99	0.99	0	
160	0.99	0.99	0.99	0	
170	0.99	0.99	0.99	0.02	
180	0.99	0.99	0.99	0.09	
190	0.99	0.99	0.99	0.22	
200	0.99	0.99	0.99	0.4	

Using the function for fitting logistic curve, derived parameters based on the inputs of *Q* and *t* are generated (Table 9). The function calculates the exceedance probability for each damage state curve at a resolution of 1 mph, which is likely fine enough for an analysis of a specific, historic storm. Appendix C list all values associated with *Q* and *t* along with the derived parameters for the logistic damage state functions for each SBT.

Table 9. Logistic curve parameters for SBT MECBL

DS	t_{half}	Q_{inf}	α
1	101.1538	0.9917	0.2160
2	108.6858	0.9909	0.2052
3	119.0418	0.9904	0.2191
4	189.5572	0.3772	0.1679

Figure 8 displays the damage state curves for SBT MECBL using the defined inputs with the logistic function. The exact process is replicated to fit the remaining 10 SBTs Appendix D. The exceedance probabilities for each damage state are inputs for a damage output estimate.

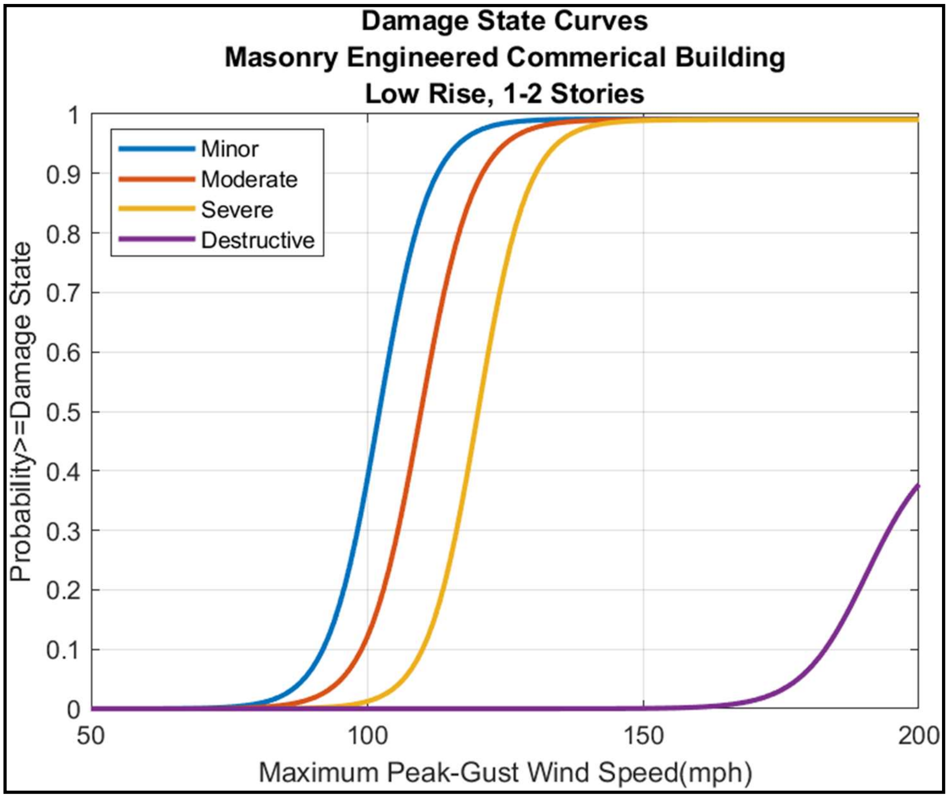


Figure 7. Modeled damage state curves for SBT MECBL utilizing a fitting logistic curve

It should be noted that the characteristics for each HAZUS SBC differ, e.g., SBCs for wood are much different than masonry. Terrain is a characteristic that appears in each SBC. For this analysis, the terrain option is set to a Suburban type of environment, because it closely resembles that found at TAFB. The remaining characteristics are less straightforward to decipher, e.g., roof cover type, window area, roof wall connection etc. Without an onsite physical examination of all 492 facilities used within this analysis, the determination of each characteristic is not feasible. Therefore, respective characteristics in each SBC are kept consistent for each SBT when choosing the appropriate figures to

remodel fragility curves. A detailed depiction of the characteristics used for each SBT can be found in Appendix B.

5.2.2 EDO Calculation

The EDO calculation starts by identifying Exceedance Probabilities (EP) associated with each damage state, based on the peak-maximum wind gust speed for a simulated storm. Next, the EPs are used to calculate each Probability Damage State (PDS), which is the height of the fragility curve at any wind value, less the height of the curve next higher damage state (Equation 2):

$$PDS_{i,j} = EP_{i,k} - EP_{j,k} \tag{2}$$

where $PDS_{i,j}$ represents the area under the curve for the referenced damage state i for SBT j; $EP_{i.k}$ depicts the EP of that damage state i for wind speed k; and $EP_{j,k}$ depicts the EP of the next increasing damage state j for wind speed k. Figure 9 shows a visual example of PDS calculations for a storm with a peak-maximum wind gust speed of 150 mph, for SBT WSF1. Each value of PDS represents the total probability of each damage state occurring for the WSF1 facility type, given the wind speed.

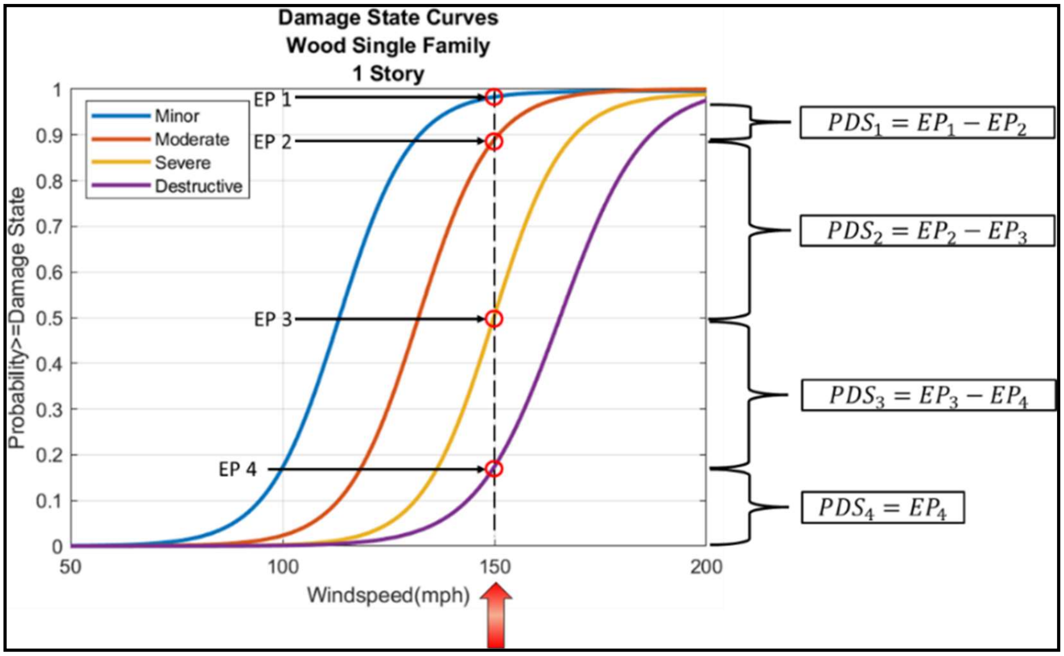


Figure 8. Depiction of Probability Damage State (PDS) equations for each level of damage for SBT WSF1. Note, PDS_4 is the curve height, because no other curves appear below it; all other PDS calculations are the difference between curve heights.

While the PDS is the probability that a facility will be in a particular damage state, it does not define the actual physical damage to the facility. Determining the physical damage requires using descriptive tables like those shown in Figure 10. The damage in Table 6.9 from the FEMA HAZUS Hurricane Model TM 2.1 shows component-level damage for facilities. For HAZUS-MH, individual component information gathered from the simulations is summarized and then used to determine the overall damage state of the facility.

Table 6-9. Damage States for Residential Construction Classes

Damage State	Qualitative Damage Description	Roof Cover Failure	Window Door Failures	Roof Deck	Missile Impacts on Walls	Roof Structure Failure	Wall Structure Failure
0	**No Damage or Very Minor Damage** Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof over, with no or very limited water penetration.	≤2%	No	No	No	No	No
1	**Minor Damage** Maximum of one broken window, door or garage door. Moderate roof cover loss that can be covered to prevent additional water entering the building. Marks or dents on walls requiring painting or patching for repair.	>2% and ≤15%	One window, door, or garage door failure	No	<5 impacts	No	No
2	**Moderate Damage** Major roof cover damage, moderate window breakage. Minor roof sheathing failure. Some resulting damage to interior of building from water	>15% and ≤50%	> one and ≤ the larger of 20% & 3	1 to 3 panels	Typically 5 to 10 impacts	No	No
3	**Severe Damage** Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water.	>50%	> the larger of 20% & 3 and ≤50%	>3 and ≤25%	Typically 10 to 20 impacts	No	No
4	**Destruction** Complete roof failure and/or, failure of wall frame. Loss of more than 50% of roof sheathing.	Typically >50%	>50%	>25%	Typically >20 impacts	Yes	Yes

Figure 9. Summarization of facility damage at each damage state level for non-engineered residential buildings; from FEMA HAZUS Hurricane Model TM 2.1 (2017)

Because there is a lack of agreement across the modes of failure (Fig. 7), and the intent of this work is to create a generalize framework, the damage determination is based on the particular component that is qualitatively determined to most influence the building's performance. For example, the facility is expected to experience between 2 and 15 percent total damage when in a minor damage state. In the case of SBT WSF1, which represents a non-engineered residential facility, the Roof Cover Failure produces more impact on the building performance than any other component, across all damage states (FEMA 2017). Therefore, the damage level of the Roof Cover Component is used to characterize the overall level of facility damage, as it likely controls or influences other areas of failure. The remaining non-engineered residential buildings, MMUH1 and MMUH2, follow an equivalent process as WSF1. SBT SPMBL and SPMBM represent

metal buildings that adhere to Table 6.55 in the TM. Fenestrations dictate the performance of these facilities, represented by the wind/door damage states. The remaining SBT relates to engineered residential and commercial buildings, as conveyed in Table 6.59 in the TM. The performance of these buildings resembles that of the formerly stated non-engineered residential buildings. Appendix E lists the two tables above depicting the facility damage linked to their SBT. Table 10 lists each SBT, and each damage state matches the facility damage (FD) value range. That is, once the PDS is calculated, a predicted FD value can be calculated.

Table 10. Total facility damage per damage state for identified TAFB SBT. Total FD per damage state is derived from the primary individual component driving building performance. *Modification factor of 1.33 applied to each damage state; the threshold damage levels defining the roof damage states are modified by a factor which is a function of the number of stories.

<table>
<tr><th>SBT</th><th>Minor (%)</th><th>Moderate (%)</th><th>Severe (%)</th><th>Destructive (%)</th><th>TM Table</th></tr>
<tr><td>CECBL</td><td rowspan="6">2 ≤ FD < 15</td><td rowspan="6">15 ≤ FD < 50</td><td rowspan="6">50 ≤ FD < 100</td><td rowspan="8">FD = 100</td><td>6.59</td></tr>
<tr><td>MECBL</td><td>6.59</td></tr>
<tr><td>MECBM</td><td>6.59</td></tr>
<tr><td>MERBL</td><td>6.59</td></tr>
<tr><td>MERBM</td><td>6.59</td></tr>
<tr><td>MMUH1</td><td>6.9</td></tr>
<tr><td>MMUH2*</td><td>2.6 ≤ FD < 19.9</td><td>19.9 ≤ FD < 66</td><td>66.5 ≤ FD < 100</td><td>6.9*</td></tr>
<tr><td>SECBL</td><td>2 ≤ FD < 15</td><td>15 ≤ FD < 50</td><td>50 ≤ FD < 100</td><td>6.59</td></tr>
</table>

SPMBL		$15 \leq FD < 33$	$33 \leq FD < 75$	$75 \leq FD \leq 100$	6.55
SPMBM					6.55
WSF1		$15 \leq FD < 50$	$50 \leq FD < 100$	$FD = 100$	6.9

FD values employed within the analysis are selected at random from a uniform distribution between the stated limits of each damage state. Applying this technique supports the notion that damaging winds and facility resistivities are pseudo-stochastic, and thus they may take on any value from within the FD range within a particular damage state.

Expected Facility Damage (EFD) describes the total percentage of structural damage sustained by a facility, due to extreme wind speeds. The sum of the products of PDS and FD for each damage state demonstrates the EFD (Equation 3):

$$EFD_{i,j} = \sum PDS_{i,j,k} \times FD_{i,j,k}$$

(3)

where $EFD_{i,j}$ corresponds to the particular facility, *i* and wind speed, *j*; $PDS_{i,j,k,}$ and $FD_{i,j,k}$ represent facility values related to the specified SBT *i*, damage state *j*, and wind speed *k*. Utilizing the established EFD in conjunction with a facility's PRV, an economic value of physical damage that each facility encounters due to the wind-induced damages (Equation 4):

$$EDO_{i,j} = EFD_{i,j} \times PRV_i \tag{4}$$

where $EDO_{i,j}$ represents the economic physical damage for a facility i, at a simulated wind speed j; $EFD_{i,j}$ depicts the percent structural damage of facility i for wind speed j, and PRV_i represents the cost in present day value of facility i.

5.3 Vulnerability

Vulnerability is calculated based on the EDO for each facility and its attributes: BCI, MDI, and Age. It is presumed that decision makers desire to limit facility vulnerability, and tend to place emphasis on protecting facilities with higher BCI (better condition), MDI (more important), EDO (more likely to be damaged) metrics, and lower Age (newer) highlighting a loss minimalization focus (Figure 11). This is an assumption and can be easily modified to account decision maker preferences.

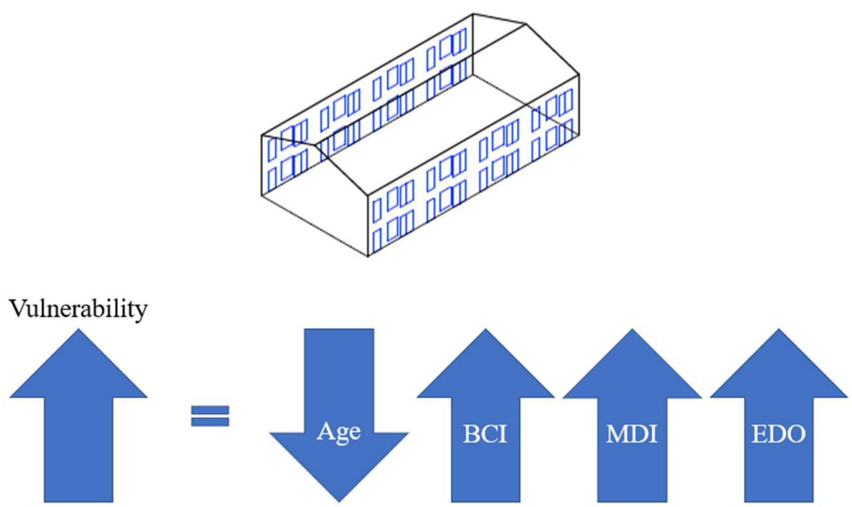


Figure 10. Vulnerability scores depend upon facility attributes—vulnerability increases as age decreases, BCI increases, MDI increases, and EDO increases.

While MDI and BCI are on consistent, 100-point scales, PRV is reported in millions of dollars, and facility age is measured in years since commissioning. To account for mismatched units, attributes are min-max normalized on a scale from 0 to 1, such that they are evenly weighted in the vulnerability model (Equation 5):

$$Vulnerability_{i,j} = Age_i \times BCI_i \times MDI_i \times EDO_{i,j} \tag{5}$$

where $Vulnerability_{i,j}$ depicts the score based on facility i and scenario j; Age_i, BCI_i, and MDI_i correspond to the normalized values of a facility i that stay constant within each scenario; and $EDO_{i,j}$ characterizes normalized values dependent upon facility i and wind speed j. After calculation, the vulnerability is min-max normalized on a scale of 0 to 1. To explore the uncertainty of the model results generated from the uniform distribution of FD within the EDO, Monte Carlo simulation is employed. Within this analysis, each wind speed scenario is replicated 1,000 times to test solution stability. From the cumulative vulnerability scores, the mean, 25th, 50th, and 75th percentile values are recorded and spatially mapped to illustrate spatial vulnerability, both in terms of solution stability (between quartiles), and the degree to which regions of vulnerability emerge with respect to exposure and facility type.

5.4 Risk

Vulnerability ignores the probability of occurrence; it answers: *What is likely to happen if an event comes to pass?* Risk requires that the recurrence interval for each categorical hurricane is known and applied to the vulnerability scores for each facility.

Risk is the product of each facility's scenario-dependent vulnerability score and recurrence interval probability (Equation 6):

$$Risk_{i,j} = Return\ Period_i \times Vulnerability_{i,j} \qquad (6)$$

where $Vulnerability_j$ is represented as the average vulnerability of all facilities within a given scenario; the $Return\ Period_i$ depicts the recurrence interval probability of each categorical storm. Risk calculation is employed for the average vulnerability of each storm's 25th, 50th, and 75th percentile to depict which categorical storm poses the most significant risk to the overall base.

VI. Results

6.1 Results Overview

The following chapter provides a sample of results produced from the application of the vulnerability and risk framework identified within the methodology section. The chapter first discusses the vulnerability of facilities from each district at TAFB. Because it is difficult to discuss the vulnerability of 492 facilities across a number of hurricane wind scenarios, the chapter then transitions to a discussion of the nature of the most vulnerable facilities (top 50), and their vulnerability with respect to changes in wind inputs. The chapter concludes with risk translation, and a portfolio analysis, based on the most vulnerable facilities, to explore to which storms the installation possesses the greatest risk. This can also be viewed as an input to "design storm" determination, as existing standards of construction for hurricane-prone areas target designing to Saffir-Simpson scale storms.

6.2 Vulnerability by District

The resulting vulnerability analysis aims to satisfy the research objective that downscales intensified natural disasters to the facility-level. The output from this analysis highlights facility vulnerability relative to all facilities located at TAFB. Figure 12 displays the vulnerability output due to hurricane wind damage from a Category 1 hurricane making landfall at Tyndall AFB. The track of the hurricane is consistent with that which maximizes the exposure of Tyndall's facilities to peak gusts.

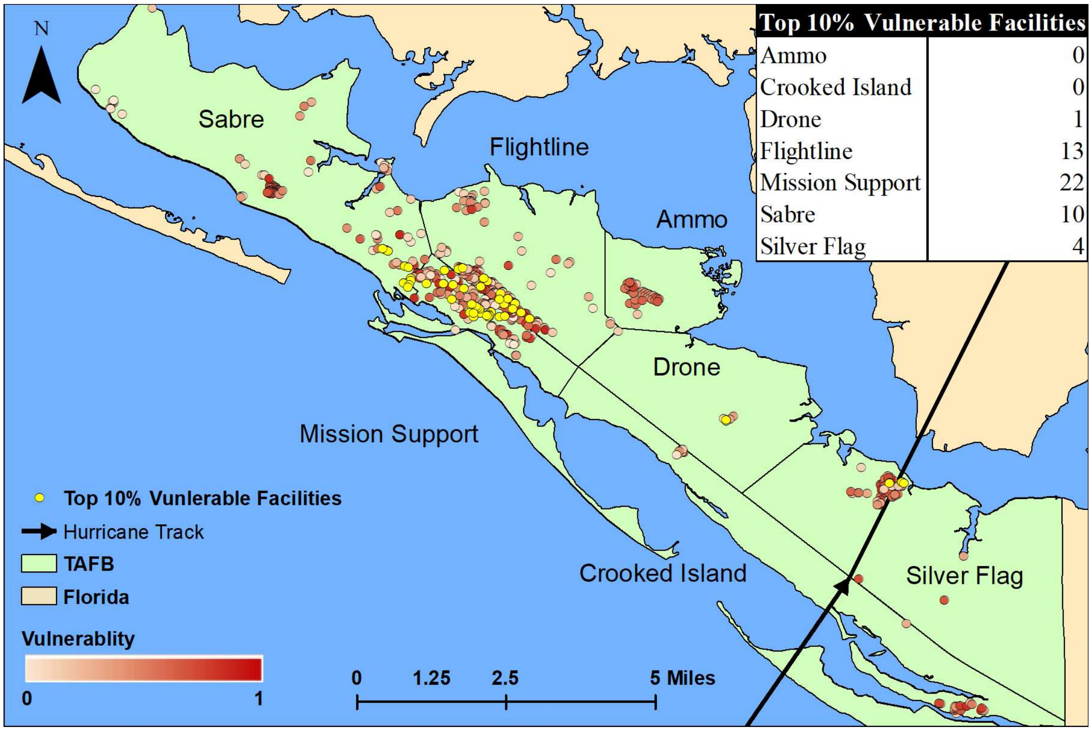


Figure 11. Facility vulnerability map for TAFB during a Category 1 (74 mph sustained winds). The top 10% of facilities are defined as those with the 50 largest vulnerability scores.

Results are shown at the 50th percentile from the Monte Carlo simulations, and are normalized (0 = lowest vulnerability, 1= highest vulnerability). In the case of a Category 1 storm, the results shows that the Mission Support district contains the most vulnerable facilities at 22. This result is expected as the Mission Support district contains the most valuable, i.e., highest average PRV, and some of the oldest facilities at TAFB. Flightline and Sabre districts contain the next highest average PRV, and as such also exhibit a high

level of vulnerability. Relative rankings for each category of storm (district-wise percent of facilities in top 10% most vulnerable at TAFB), are provided below (Table 11).

When wind speeds are increased to a Category 2 storm (96 mph sustained winds), the results change slightly (Figure 13). Again, the districts that contain the most vulnerable facilities stay consistent, but the facility distribution changes. Previously, 70% of the most vulnerable resided within Mission Support and Flightline, but this percentage now increases to 84%. This finding follows the same pattern as in the previous scenario in that the districts with the higher average PRV facility tend to be more vulnerable.

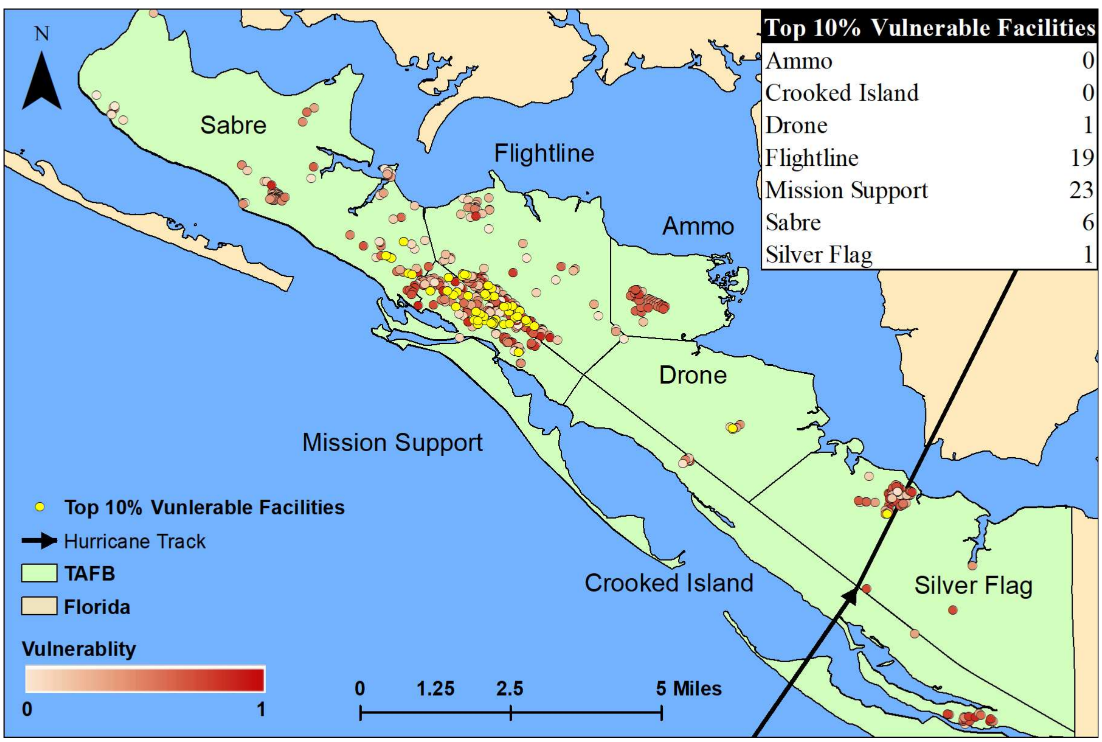


Figure 12. Facility vulnerability map for TAFB during a Category 2 hurricane with 96 mph sustained wind speed.

Another perspective to take in account is the percent of top 10% vulnerable facilities, relative the number of facilities within a district (Table 11). From Table 11, the Mission Support district is the most vulnerable district and carries this same distinction across storm categories. It should be noted that some districts are sparsely populated, which impacts the relative percentages reported in the table. For example, the Drone district contains only six facilities, and thus the one facility in the top 10% of vulnerable facilities skews its appearance among the others. Ultimately, the inter-category stability of relative percentages, at and beyond Category 3, suggests that while vulnerability increases at the facility level, the rank order of vulnerable facilities is stable.

Table 11. Percent of top 10 vulnerable facilities proportionate to the number of facilities per district.

District	Cat 1 (%)	Cat 2 (%)	Cat 3 (%)	Cat 4 (%)	Cat 5 (%)
Ammo	0	0	0	0	0
Crooked Island	0	0	0	0	0
Drone	16.67	16.67	16.67	16.67	16.67
Flightline	8.72	12.75	14.09	12.75	12.75
Mission Support	19.30	20.18	17.54	19.30	19.30
Sabre	9.80	6.12	7.14	7.14	7.14
Silver Flag	7.14	1.79	1.79	1.79	1.79

This is validated by mapping vulnerabilities of facilities from storm-to-storm (Figure 14). The Pearson Type II coefficient of determination reveals that the most variance in outcome is experienced between a Category 1 and 2 ($r^2 = 0.70$), though the relationship is likely better fit by logistic regression. The subsequent comparisons, e.g.,

Category 2 and 3, etc., show decreasing inter-storm variance ($r^2 > 0.96$). This strengthens the notion that the facility vulnerability profile stays consistent across each storm, at least for the most vulnerable facilities, which are those most likely to be adapted first.

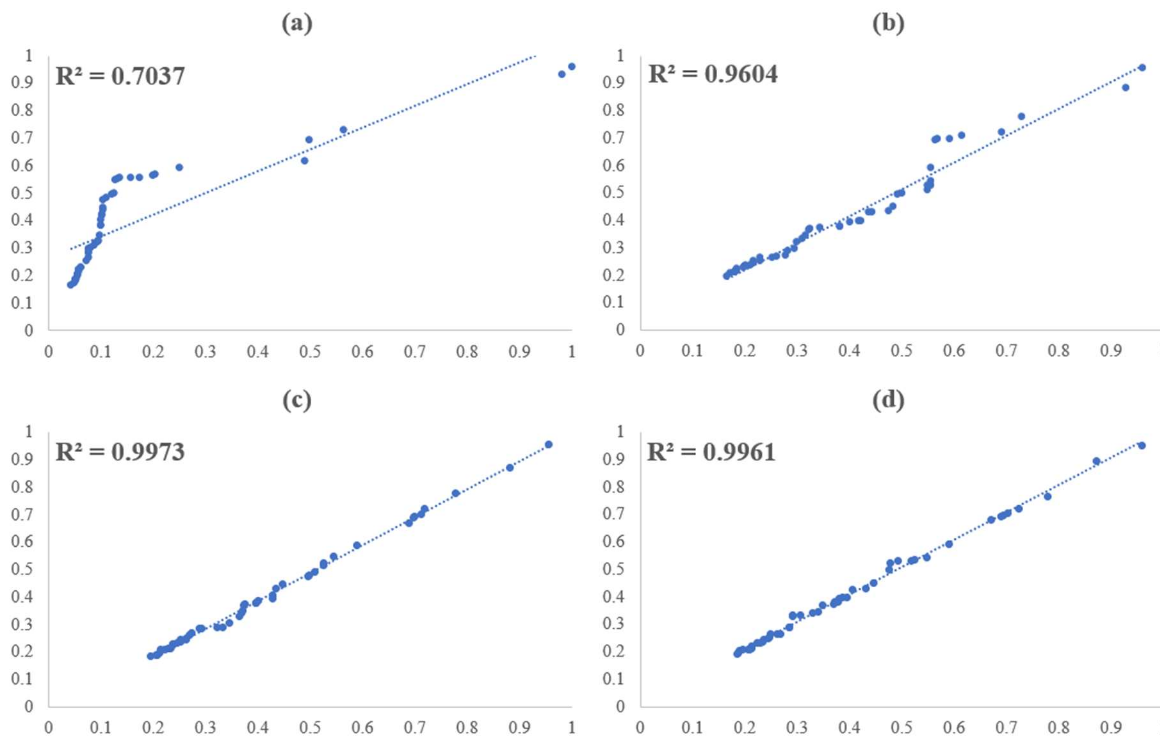


Figure 13. Vulnerability comparison of top 10 percent of facility across increasing categorical storms where comparisons are (a) Category 1 & 2, (b) Category 2 & 3, (c) Category 3 & 4, and (d) Category 4 & 5.

6.3 Vulnerability by Facility

It is also important to view the results through the lens of district-level vulnerability, as the number of stakeholders across and installation are likely to favor

adaptation decisions at this level, and it provides a deeper understanding of the results in the context of the Air Force mission (Table 12). Within a Category 1 hurricane, the top 5 vulnerable facilities reside in the Flightline and Drone districts, and each of those facilities are classified as hangars that support mission essential aircraft. This stands to reason, as the output here lines up with the logical argument that these types of facilities are the most vulnerable because of their direct relation to the primary mission of the Air Force; generating airpower.

At more intense categories of storms, this outcome does not hold. This is a function of the relationship between MDI and PRV. For example, the number of Mission Support facilities that occupy top-ten positions at and beyond Category 3 is a reflection of increasing damage to facilities large PRVs, and only slightly lower MDIs compared to Flightline and Drone districts.

Once the wind speeds reach a Category 3 level hurricane, no hangars exist within the top 10, and the profile represents facilities with a variety of different mission sets that indirectly support aircraft generation, such as the gym, medical facility, flight simulator, and communication facility. Furthermore, the profile remains the same through a Category 5 hurricane, which again supports the notion that as the wind speeds increase before Category 3, the vulnerability profile remains consistent.

Table 12. Top 10 vulnerability facility comparisons per district across categorical storm scenarios. Note: Most vulnerable facility rankings are stable for Category 3-5.

Rank	1	2	3	4	5
1	Flightline	Flightline	Flightline	Flightline	Flightline
2	Flightline	Flightline	Mission Support	Mission Support	Mission Support
3	Drone	Flightline	Sabre	Sabre	Sabre
4	Flightline	Mission Support	Flightline	Flightline	Flightline
5	Flightline	Sabre	Flightline	Flightline	Flightline
6	Mission Support	Mission Support	Mission Support	Mission Support	Mission Support
7	Mission Support	Flightline	Mission Support	Mission Support	Mission Support
8	Mission Support	Flightline	Sabre	Sabre	Sabre
9	Mission Support	Mission Support	Flightline	Flightline	Flightline
10	Mission Support	Drone	Mission Support	Mission Support	Mission Support

6.4 Risk

To progress beyond vulnerability—to risk—the recurrence interval for each categorical hurricane must be determined and applied. The modeled results of vulnerability depict what happens to the facilities at TAFB once a storm makes landfall in the region. In Figure 15, the risk is captured by taking the average vulnerability scores of top 10% most vulnerable facilities across each storm category and multiplying each interquartile vulnerability estimate (25^{th}, 50^{th}, and $75^{th)}$ by the storm category's return period.

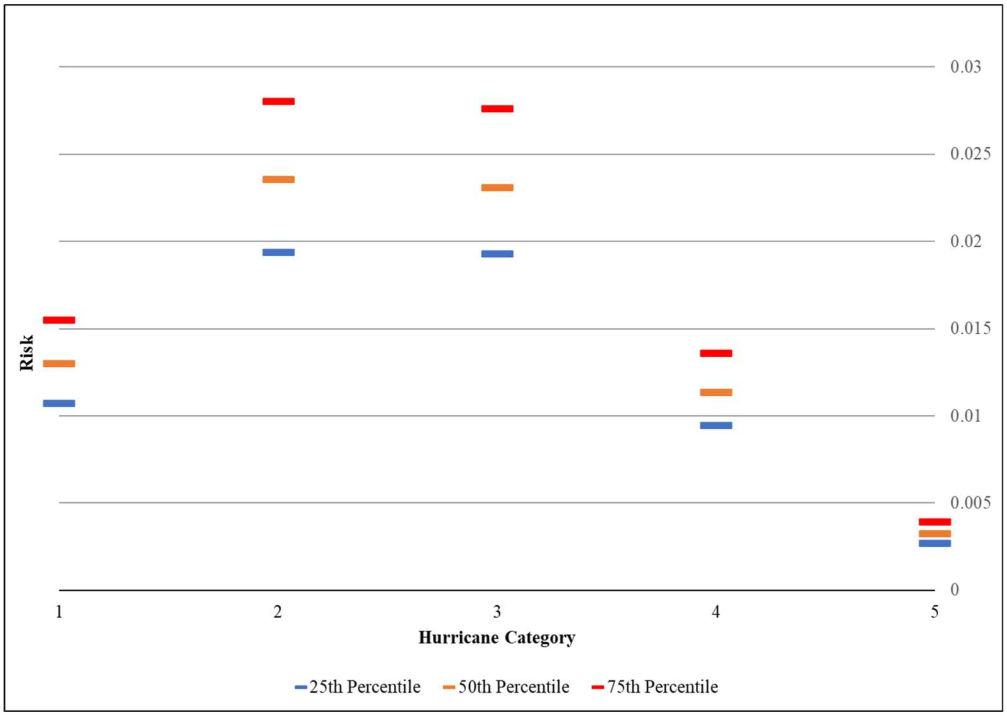


Figure 14. Quantified risk per categorical storm.

The risk profile for TAFB shows that Category 2 and 3 storms are of greatest, and most uncertain risk to the installation. The uncertainty of the outputs, at any category, are largely the function of the shape damage state curves from the 11 SBTs. The wind speeds for a Category 2 and Category 3 storm represent the steepest sections of all damage state curves, which is the reason for the large uncertainty in estimates (Fig. 5). Even with the high degree of risk uncertainty in Category 2 and 3, the 25th percentile estimates are higher than the 75th percentile estimate for any other category of storm. This suggests no less than 75% of Category 2 and 3 storms will have greater risk than any other storm category. Furthermore, the elevated risk associated with these same categories has to do with the relatively frequent recurrence of these storm events and the

high level of vulnerability (damage) projected. That is, at Category 2 and 3 wind levels, the cumulative damage and recurrence combinations are great enough to outweigh the catastrophic damage at larger categories with orders of magnitude smaller recurrence. These results can help inform design standard decisions for installations looking to adapt prior to the occurrence of a storm (see Discussion).

VII. Discussion

7.1 Discussion Overview

The goal of this research was to create a framework for practitioners to help decision makers calculate and visualize facility-level risk. This is accomplished by downscaling the environmental aspects of extreme events to facility-level impacts. Application of the framework with the facilities at TAFB demonstrated the possibility of coupling multiple existing data bases with multi-hazards tools to identify areas deemed highly vulnerable or at risk from the threat of an extreme weather event. This chapter focuses on interpretating and examining the implications of the results.

7.2 Vulnerability

When determining districts that would be categorized as vulnerable, one of the major findings was that the most vulnerable areas contained facilities with characteristics that resembled a high economic loss potential, lower age, and high mission importance. Knowing these characteristics arms decision makers with a profile through which to identify facilities classified as vulnerable, and to consider how a weighted model might be useful, should decision makers prefer to favor any input parameter. Here, no parameter weighting schemes were tested and thus the results are the equivalent of equal weighting of all parameters: BCI, Age, MDI, and PRV.

An additional finding was that as the wind speeds exceeded Category 2, the facility vulnerability profile stayed consistent, in that the relative ranking of facilities in

the top 10% (n = 50 facilities) remained unchanged. What this implies is that when decision makers employ adaptation strategies for those areas, they can be confident in the fact that profile will not change when faced with future intensified storms. This analysis included only these facilities to limit the complexity of the presentation of results, and as a reflect those adaptations of 50 facilities represents likely decades worth of planning, engineering, and construction. However, below to top 10% there are changes in the vulnerability profiles between storm categories, which suggests that comparably parameterized facilities do, in fact, reorder.

For assessing the individual facilities that are most vulnerable across storm categories, the initial expectations were that facilities that are directly tied to an aircraft would be ranked highest. At a Category 1 hurricane, the expectations hold true, in that hangars were the type of facilities deemed most vulnerable. As the categorical level of hurricane increased though, those facilities' vulnerabilities rise but not at the rate of other facilities. Beginning with a Category 2 storm, results start to show that facilities indirectly tied to the aircraft are now most vulnerable. The shared characteristic for these facilities is that they are low in age, and costly. Viewed, from an engineer's perspective, this could be seen as logical because of the desire to avoid losses associated with rebuilding or repairing the newest and most valuable facilities. However, as mentioned above, weighting of facility parameters based on different logic could produce different outcomes. Likely, weighting scenarios could be produced as part of a deliberative process or agreed upon by evaluating the outputs of various weighting schemes.

7.3 Risk

Once the facilities that are vulnerable from an extreme event are identified, they can be translated to risk by using return periods. quantifying risk, which is the product of vulnerability and probability of occurrence, design storms can be identified. From this research, the results indicate that the design level of storm could be Category 2 or 3 if decision makers value balancing risk with adaptation cost. Clearly, reducing the vulnerability of a Category 5 storm, or larger, will occur at the greatest cost. And, while decision makers may choose this risk-averse approach—adapt to the strongest storm possible—this ignores that impact of return period. In other words, a decision to view a Category 5 storm as the design event, may result in making preparations for an event that may never come to pass.

Performing analyses such as these in anticipation of future events enables decision makers to consider and balance the tradeoffs between risk and adaptation costs and options. Still, at the current time, there is no clear mechanism that supports the translation of this type of analysis to planning, design, and construction or facility adaptations. And, even with a SEED or EO-like lever to drive adaptation planning and AFCAMP scoring preference, more analysis is needed. A study such as this highlights that greater spatial employment as well as investigation of other threats emanating from hurricanes, e.g. flooding, and risks posed by other extreme natural events is required to more-fully address and respond to extreme-event risk.

VIII. Conclusion

7.1 Conclusion of Research

This research produced a framework for the identification of vulnerability and risk at the facility level, in order to help leaders plan, prepare, and adapt for future, intensified natural threats. To accomplish this, the focus centered around the following objectives:

1. Determine and consolidate relevant existing data, to characterize facility overall condition, economic value, and mission importance.
2. Apply existing frameworks linking the hazard to the system to calculate extreme-event vulnerability and risk at the facility-level.
3. Develop spatiotemporal maps of vulnerability and risk to visualize zones most susceptible to support the advancement of adaptation policies to mitigate threats.

The first objective was accomplished through a review of existing research and Chapter 2, and the application within Chapter 4. The first step in accomplishing this objective was to combine data from multiple data sets into one single data base. Within this data base variables were captured that helped to characterize vulnerability and risk, determine the economic damage impact when exposed to an extreme event, and the mapping of the indexes geographically. When characterizing vulnerability and risk from available data, the determination was made in to use variables related to the facilities Age, MDI, BCI, and PRV for two reasons 1) the data was readily available within existing AF data bases and 2) the data characterizes the importance of a facility to decision makers at the installation level. Data obtained from the BUILDER report aided

in linking the facility to impact component of the assessment by linking each facility to a set of established wind damage states curves within HAZUS. Lastly, the latitude and longitude coordinates obtained from RP records enabled the mapping of facility vulnerability and risk with GIS software.

The remaining two objectives were accomplished in the Chapters 5 and 6 by developing a framework that utilized the data obtain from accomplishing Objective 1 and implementing it as a case study analysis for TAFB. HAZUS damage state curves were used to estimate the economic damage within each scenario. Those damages were combined with MDI, BCI, and Age to determine facility level vulnerability. From there risk was then calculated using vulnerability outputs in combination with annual expected return periods. The results demonstrated the capability of determining those facilities susceptible to the extreme event allowing installation planners to chart a path forward for adaptation solutions.

7.2 Significance of Research

The significance of this research is the development of a facility-level vulnerability and risk framework that Air Force asset managers that can be applied at a local level. The use of this framework allows for base-level asset managers to determine those facilities highest at risk to extreme weather events. The use of the framework becomes even more important as adaptations are costly and will need to be attractive to project allocation models (high return on investment) to be funded. Still, forward-looking, climate-related projects are prospective, in that the benefits are actually

presented as cost avoidance, should an extreme event come to pass. There is inherent risk in adapting for an uncertain event magnitude and frequency, and if these projects are to be prioritized, there must be paradigm shift in project scoring, and one that incorporates approaches such as the one presented here. The approach used within this research presents the groundwork for how existing tools used in climate projections can be combined with readily available data and extreme weather damage estimation.

7.3 Limitations and Future Work

The primary limitations of this research centered around quality inconsistencies existing data bases. The majority of the data within these data bases are obtained through reports created or populated by facility-level asset managers. Multiple asset managers could be tasked with capture the data, and as such, data collect is inconsistently populated, maintained, and referenced. Furthermore, facility data used in the developed vulnerability/risk database is reflective of the time period before the landfall of Hurricane Michael in 2018. Therefore, the established facility profile is not fully reflective of the current facilities at TAFB, as current renovations are still ongoing, and source databases have not been updated.

The framework of the vulnerability model assumes that all variables are equally weighted, and as such carry the same importance. For example, EDO, which captures the economic cost of damage to the facility, would be considered more important than the facility age. Future work would need to include a process for which to weight the decision parameters of the model such that it captures the importance aligned with that of

the decision-maker's preferences. The likely scenario would be transforming the vulnerability model from one that is multiplicative to additive, which would be potential easier to adapt. Futhermore, the presentation of the model could be seen as overly constrained. A refined model would only include factors based on MDI and EDO. Within this type of model Age would not be used, and BCI would be captured within EDO.

While there exists discussion on the topic that hurricanes are expected to increase in intensity due to climate change, this model only analyzes the wind speeds up to a Category 5 (157+ mph). This is done in part because at a Category 5 hurricane the impact relates close to total destruction. While scenarios of future intensified hurricanes might reach higher wind speeds e.g., 200 mph, which illustrates a numerical difference from 157 mph, the result is still the same in terms of damage from wind speed. The main influence for modeling these type of future storms derives from the recurrence interval. Further studies should focus on how the change in frequency of major hurricanes to accurately reflect risk from future climate change scenarios.

Furthermore, the work performed here is tied to fact that only wind speed is considered. Hurricanes, like many events, are multi-hazard. Future work should address how flooding affects vulnerability and risk, and how the coupling of flood and wind models changes vulnerability and risk at the facility and installation level. Additionally, studies should focus on other risks, e.g., wildfire, recurrent tidal flooding, flooding not

tied to hurricanes, and seismic events, to more clearly determine risks from installation to installation, and across risk type.

Lastly, this work does not address facility resilience or robustness, and does not address adaptation pathways or portfolios. A more complete analysis of the wind-threat pathway would provide cost-analyzed, temporally-aligned portfolio options that detail the cost and timing of adaptation options that reduce the risks presented here. Clearly, there must be some policy lever or levers available to planners and planners that provides a demand signal for these types of analyses and long-term planning. As discussed in the Literature Review, SEEDs and EOs present a template for programs that tackle location, mission, and outcome-based facility design and construction needs for the Air Force. Using policy levers like these could provide an incentive to installation-level engineers, and allow progress toward addressing natural hazard risk.

Appendix A.

Table 13.11. HAZUS-MH Specific Building Types

SBT	Description
WSF1	Wood, Single Family, One Story
WSF2	Wood, Single Family, Two or More Stories
WMUH1	Wood, Multi-Unit Housing, One Story
WMUH2	Wood, Multi-Unit Housing, Two Stories
WMUH3	Wood, Multi-Unit Housing, Three or More Stories
MSF1	Masonry, Single Family, One Story
MSF2	Masonry, Single Family, Two or More Stories
MMUH1	Masonry, Multi-Unit Housing, One Story
MMUH2	Masonry, Multi-Unit Housing, Two Stories
MMUH3	Masonry, Multi-Unit Housing, Three or More Stories
MLRM1	Masonry, Low-Rise Strip Mall, Up to 15 Feet
MLRM2	Masonry, Low-Rise Strip Mall, More than 15 Feet
MLRI	Masonry, Low-Rise Industrial/Warehouse/Factory Buildings
MERBL	Masonry, Engineered Residential Building, Low-Rise (1-2 Stories)
MERBM	Masonry, Engineered Residential Building, Mid-Rise (3-5 Stories)
MERBH	Masonry, Engineered Residential Building, High-Rise (6+ Stories)
MECBL	Masonry, Engineered Commercial Building, Low-Rise (1-2 Stories)
MECBM	Masonry, Engineered Commercial Building, Mid-Rise (3-5 Stories)
MECBH	Masonry, Engineered Commercial Building, High-Rise (6+ Stories)
CERBL	Concrete, Engineered Residential Building, Low-Rise (1-2 Stories)
CERBM	Concrete, Engineered Residential Building, Mid-Rise (3-5 Stories)
CERBH	Concrete, Engineered Residential Building, High-Rise (6+ Stories)
CECBL	Concrete, Engineered Commercial Building, Low-Rise (1-2 Stories)
CECBM	Concrete, Engineered Commercial Building, Mid-Rise (3-5 Stories)
CECBH	Concrete, Engineered Commercial Building, High-Rise (6+ Stories)
SPMBS	Steel, Pre-Engineered Metal Building, Small
SPMBM	Steel, Pre-Engineered Metal Building, Medium
SPMBL	Steel, Pre-Engineered Metal Building, Large
SERBL	Steel, Engineered Residential Building, Low-Rise (1-2 Stories)
SERBM	Steel, Engineered Residential Building, Mid-Rise (3-5 Stories)
SERBH	Steel, Engineered Residential Building, High-Rise (6+ Stories)
SECBL	Steel, Engineered Commercial Building, Low-Rise (1-2 Stories)
SECBM	Steel, Engineered Commercial Building, Mid-Rise (3-5 Stories)
SECBH	Steel, Engineered Commercial Building, High-Rise (6+ Stories)
MHPHUD	Manufactured Home, Pre-HUD
MH76HUD	Manufactured Home, 1976 HUD
MH94HUD-I	Manufactured Home, 1994 HUD - Wind Zone I
MH94HUD-II	Manufactured Home, 1994 HUD - Wind Zone II
MH94HUD-III	Manufactured Home, 1994 HUD - Wind Zone III

Complete list of all Specific Building Types (SBT) as defined within the FEMA HAZUS Hurricane Model Technical Manual 2.1

Appendix B.

SBT WSF1 Damage State Characteristics	
Roof Shape	Gable
Secondary Water Resistance	No
Roof Deck Attachment	6d @ 6"/12"
Roof-Wall Connection	Strap
Garage, Houses w/out Shutters	None
Shutters	No
Terrain	Suburban

SBT SPMBM Damage State Characteristics	
Roof Deck Age	New or Average
Shutters	No
Metal Roof Deck Attachment	Standard
Terrain	Suburban

SBT SPMBL Damage State Characteristics	
Roof Deck Age	New or Average
Shutters	No
Metal Roof Deck Attachment	Standard
Terrain	Suburban

SBT MMUH1 Damage State Characteristics	
Roof Shape	Gable
Secondary Water Resistance	Yes
Roof Deck Attachment	8d @ 6"/12"
Roof Wall Connection	Strap
Shutters	No
Mason Reinforcing	Yes
Terrain	Suburban

SBT MMUH2 Damage State Characteristics	
Roof Shape	Gable
Secondary Water Resistance	Yes
Roof Deck Attachment	8d @ 6"/12"
Roof Wall Connection	Strap
Shutters	No
Mason Reinforcing	Yes
Terrain	Suburban

SBT MERBM Damage State Characteristics	
Roof Cover Type	BUR
Window Area	Medium
Shutters	No
Wind Debris	Res/Comm
Terrain	Suburban
Metal Roof Deck Attachment	Standard

SBT MERBL Damage State Characteristics	
Roof Cover Type	BUR
Window Area	Medium
Shutters	No
Wind Debris	Res/Comm
Terrain	Suburban
Metal Roof Deck Attachment	Standard

SBT MECBM Damage State Characteristics	
Roof Cover Type	BUR
Window Area	Medium
Shutters	No
Wind Debris	Res/Comm
Terrain	Suburban
Metal Roof Deck Attachment	Standard

SBT MECBL Damage State Characteristics	
Roof Cover Type	BUR
Window Area	Medium
Shutters	No
Wind Debris	Res/Comm
Terrain	Suburban
Metal Roof Deck Attachment	Standard

SBT CECBL Damage State Characteristics	
Roof Cover Type	BUR
Window Area	Medium
Shutters	No
Wind Debris	Res/Comm
Terrain	Suburban
Metal Roof Deck Attachment	Standard

Appendix C.

Parameters t and Q for SBT WSF1					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.0001	0	0	0	
90	0.06	0	0	0	
100	0.2	0.01	0	0	
110	0.4	0.09	0	0	
120	0.7	0.23	0.001	0	
130	0.91	0.50	0.09	0.01	
140	0.98	0.73	0.27	0.05	
150	0.99	0.90	0.57	0.20	
160	0.99	0.99	0.78	0.41	
170	0.99	0.99	0.91	075	
180	0.99	0.99	0.97	0.81	
190	0.99	0.99	0.98	0.9	
200	0.99	0.99	0.99	0.99	

Logistic curve parameters Damage States 1 - 4 for WSF1			
DS	*thalf*	*Qinf*	*alpha*
1	112.3144	0.9963	0.1177
2	131.0601	1.0002	0.1166
3	148.6855	0.9908	0.1192
4	164.5572	1.0061	0.1005

<table>
<tr><th colspan="6">Parameters t and Q for SBT SPMBM</th></tr>
<tr><th>t (mph)</th><th>DS 1</th><th>DS 2</th><th>DS 3</th><th>DS 4</th><th></th></tr>
<tr><td>0</td><td>0</td><td>0</td><td>0</td><td>0</td><td rowspan="14">(Q) Probability >= Damage State</td></tr>
<tr><td>80</td><td>0.001</td><td>0</td><td>0</td><td>0</td></tr>
<tr><td>90</td><td>0.02</td><td>0.01</td><td>0.001</td><td>0</td></tr>
<tr><td>100</td><td>0.12</td><td>0.11</td><td>0.05</td><td>0</td></tr>
<tr><td>110</td><td>0.35</td><td>0.34</td><td>0.11</td><td>0</td></tr>
<tr><td>120</td><td>0.58</td><td>0.56</td><td>0.29</td><td>0</td></tr>
<tr><td>130</td><td>0.78</td><td>0.77</td><td>0.55</td><td>0</td></tr>
<tr><td>140</td><td>0.86</td><td>0.85</td><td>0.74</td><td>0.001</td></tr>
<tr><td>150</td><td>0.92</td><td>0.91</td><td>0.85</td><td>0.02</td></tr>
<tr><td>160</td><td>0.97</td><td>0.96</td><td>0.88</td><td>0.1</td></tr>
<tr><td>170</td><td>0.98</td><td>0.97</td><td>0.93</td><td>0.21</td></tr>
<tr><td>180</td><td>0.99</td><td>0.98</td><td>0.97</td><td>0.39</td></tr>
<tr><td>190</td><td>0.99</td><td>0.99</td><td>0.98</td><td>0.58</td></tr>
<tr><td>200</td><td>0.99</td><td>0.99</td><td>0.99</td><td>0.65</td></tr>
</table>

Logistic curve parameters Damage States 1 - 4 for SPMBM			
DS	*thalf*	*Qinf*	*alpha*
1	117.2950	0.9794	0.1050
2	117.9826	0.9738	0.1044
3	128.6986	0.9686	0.0961
4	178.2895	0.7195	0.1027

Parameters t and Q for SBT SPMBL					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.05	0.05	0	0	
90	0.22	0.21	0.01	0	
100	0.5	0.49	0.1	0	
110	0.73	0.72	0.35	0	
120	0.95	0.94	0.59	0	
130	0.91	0.92	0.78	0	
140	0.98	0.97	0.88	0.02	
150	0.99	0.98	093	0.09	
160	0.99	0.99	0.96	0.28	
170	0.99	0.99	0.98	0.5	
180	0.99	0.99	0.99	0.69	
190	0.99	0.99	0.99	0.82	
200	0.99	0.99	0.99	0.91	

Logistic curve parameters Damage States 1 - 4 for SPMBL			
DS	*thalf*	*Qinf*	*alpha*
1	99.8170	0.9891	0.1522
2	100.0679	0.9864	0.1476
3	116.9401	0.9741	0.1179
4	169.6251	0.9504	0.0989

Parameters t and Q for SBT SECBL					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.02	0.001	0	0	
90	0.12	0.002	0	0	
100	0.41	0.15	0.001	0	
110	0.89	0.56	0.12	0	
120	0.98	0.9	0.55	0	
130	0.99	0.99	0.9	0	
140	0.99	0.99	0.99	0	
150	0.99	0.99	0.99	0	
160	0.99	0.99	0.99	0	
170	0.99	0.99	0.99	0.02	
180	0.99	0.99	0.99	0.09	
190	0.99	0.99	0.99	0.22	
200	0.99	0.99	0.99	0.4	

Logistic curve parameters Damage States 1 - 4 for SECBL			
DS	*thalf*	*Qinf*	*alpha*
1	101.1538	0.9917	0.2160
2	108.6858	0.9909	0.2052
3	119.0418	0.9904	0.2191
4	189.5572	0.4545	0.1679

Parameters t and Q for SBT MMUH2					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.01	0	0	0	
90	0.05	0	0	0	
100	0.2	0.01	0	0	
110	0.42	0.05	0	0	
120	0.69	0.16	0.001	0	
130	0.89	0.36	0.02	0	
140	0.96	0.59	0.11	0	
150	0.99	0.79	0.37	0	
160	0.99	0.92	0.51	0.001	
170	0.99	0.97	0.69	0.02	
180	0.99	0.98	0.88	0.13	
190	0.99	0.99	0.92	0.31	
200	0.99	0.99	0.98	0.59	

Logistic curve parameters Damage States 1 - 4 for MMUH2			
DS	*thalf*	*Qinf*	*alpha*
1	112.5569	0.9920	0.1187
2	136.0627	0.9914	0.1032
3	159.1233	0.9913	0.0922
4	189.4451	0.6467	0.1779

Parameters t and Q for SBT MMUH1					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.01	0	0	0	
90	0.05	0	0	0	
100	0.2	0.01	0	0	
110	0.42	0.05	0	0	
120	0.69	0.16	0.001	0	
130	0.89	0.36	0.02	0	
140	0.96	0.59	0.11	0	
150	0.99	0.79	0.37	0	
160	0.99	0.92	0.51	0.001	
170	0.99	0.97	0.69	0.02	
180	0.99	0.98	0.88	0.13	
190	0.99	0.99	0.92	0.31	
200	0.99	0.99	0.98	0.59	

Logistic curve parameters Damage States 1 - 4 for MMUH1			
DS	*thalf*	*Qinf*	*alpha*
1	112.5569	0.9920	0.1187
2	136.0627	0.9914	0.1032
3	159.1233	0.9913	0.0922
4	189.4451	0.6467	0.1779

Parameters t and Q for SBT MERBM					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.05	0.001	0	0	
90	0.19	0.02	0	0	
100	0.52	0.2	0	0	
110	0.88	0.64	0	0	
120	0.98	0.95	0.28	0	
130	0.99	0.99	0.73	0	
140	0.99	0.99	0.96	0.001	
150	0.99	0.99	0.98	0.01	
160	0.99	0.99	0.99	0.09	
170	0.99	0.99	0.99	0.22	
180	0.99	0.99	0.99	0.48	
190	0.99	0.99	0.99	0.78	
200	0.99	0.99	0.99	0.83	

Logistic curve parameters Damage States 1 - 4 for MERBM			
DS	*thalf*	*Qinf*	*alpha*
1	98.9622	0.9922	0.1709
2	106.9004	0.9916	0.2091
3	124.8302	0.9898	0.2120
4	177.9630	0.8831	0.1407

Parameters t and Q for SBT MERBL					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.03	0.01	0	0	
90	0.12	0.002	0	0	
100	0.41	0.15	0.001	0	
110	0.8	0.56	0.12	0	
120	0.98	0.9	0.52	0	
130	0.99	0.98	0.91	0	
140	0.99	0.99	0.98	0	
150	0.99	0.99	0.99	0	
160	0.99	0.99	0.99	0	
170	0.99	0.99	0.99	0.02	
180	0.99	0.99	0.99	0.08	
190	0.99	0.99	0.99	0.21	
200	0.99	0.99	0.99	0.42	

Logistic curve parameters Damage States 1 - 4 for MERBL			
DS	*thalf*	*Qinf*	*alpha*
1	101.8160	0.9922	0.1770
2	108.6816	0.9903	0.2041
3	119.4409	0.9906	0.2201
4	191.0036	0.4948	0.1748

Parameters t and Q for SBT MECBM					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.05	0	0	0	
90	0.19	0.02	0	0	
100	0.52	0.2	0	0	
110	0.89	0.66	0.01	0	
120	0.99	0.95	0.28	0	
130	0.99	0.99	0.73	0	
140	0.99	0.99	0.95	0	
150	0.99	0.99	0.98	0.03	
160	0.99	0.99	0.99	0.14	
170	0.99	0.99	0.99	0.37	
180	0.99	0.99	0.99	0.59	
190	0.99	0.99	0.99	0.78	
200	0.99	0.99	0.99	0.88	

Logistic curve parameters Damage States 1 - 4 for MECBM			
DS	*thalf*	*Qinf*	*alpha*
1	99.3792	0.9950	0.1745
2	106.0475	0.9901	0.2273
3	124.5143	0.9899	0.2065
4	175.1706	0.9285	0.1163

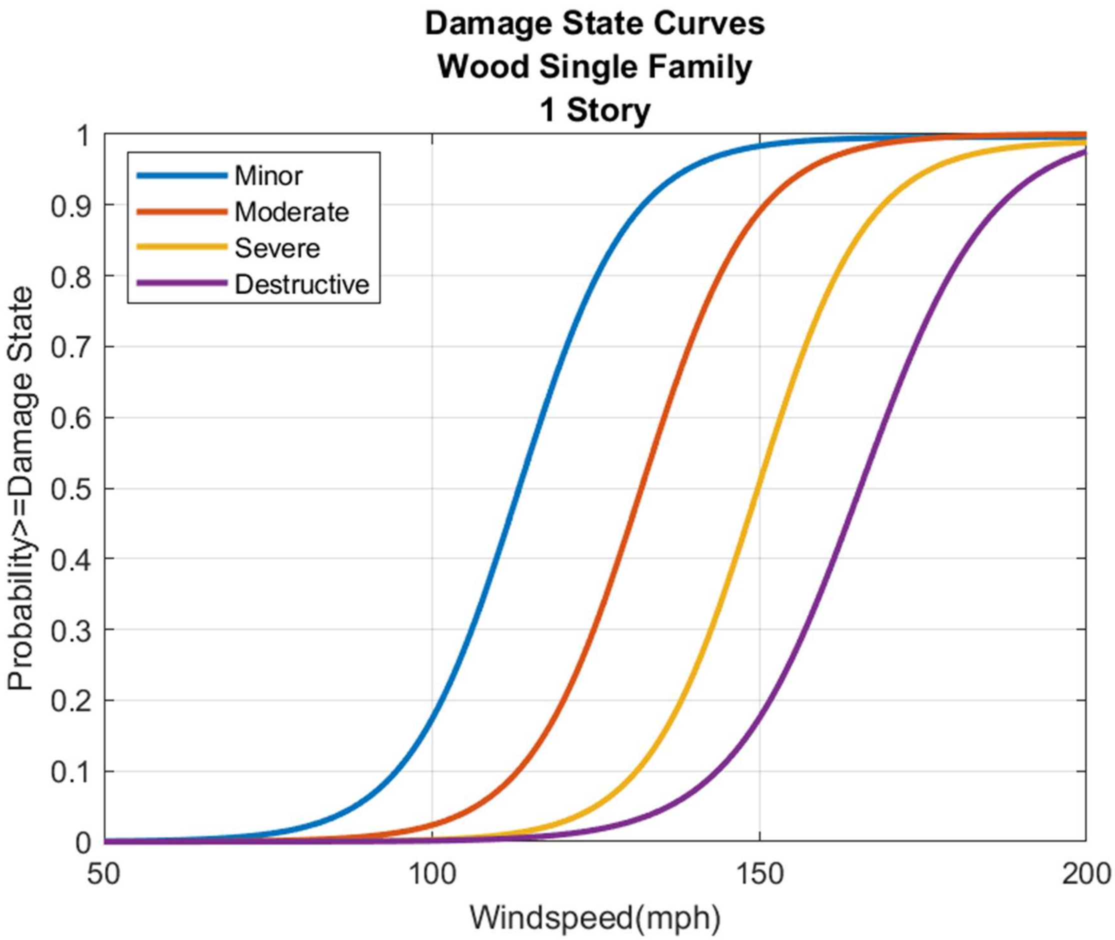
Parameters t and Q for SBT MECBL					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.02	0.001	0	0	
90	0.12	0.002	0	0	
100	0.41	0.15	0.001	0	
110	0.89	0.56	0.12	0	
120	0.98	0.9	0.55	0	
130	0.99	0.99	0.9	0	
140	0.99	0.99	0.99	0	
150	0.99	0.99	0.99	0	
160	0.99	0.99	0.99	0	
170	0.99	0.99	0.99	0.02	
180	0.99	0.99	0.99	0.09	
190	0.99	0.99	0.99	0.22	
200	0.99	0.99	0.99	0.4	

Logistic curve parameters Damage States 1 - 4 for MECBL			
DS	*thalf*	*Qinf*	*alpha*
1	101.1538	0.9917	0.2160
2	108.6858	0.9909	0.2052
3	119.0418	0.9904	0.2191
4	189.5572	0.3772	0.1679

Parameters t and Q for SBT CECBL					
t (mph)	DS 1	DS 2	DS 3	DS 4	
0	0	0	0	0	**(Q) Probability >= Damage State**
80	0.02	0.001	0	0	
90	0.12	0.002	0	0	
100	0.41	0.15	0.001	0	
110	0.89	0.56	0.12	0	
120	0.98	0.9	0.55	0	
130	0.99	0.99	0.9	0	
140	0.99	0.99	0.99	0	
150	0.99	0.99	0.99	0	
160	0.99	0.99	0.99	0	
170	0.99	0.99	0.99	0.002	
180	0.99	0.99	0.99	0.05	
190	0.99	0.99	0.99	0.12	
200	0.99	0.99	0.99	0.19	

Logistic curve parameters Damage States 1 - 4 for CECBL			
DS	*thalf*	*Qinf*	*alpha*
1	101.1538	0.9917	0.2160
2	108.6858	0.9909	0.2052
3	119.0418	0.9904	0.2191
4	190.8758	0.2527	0.1439

Appendix D.



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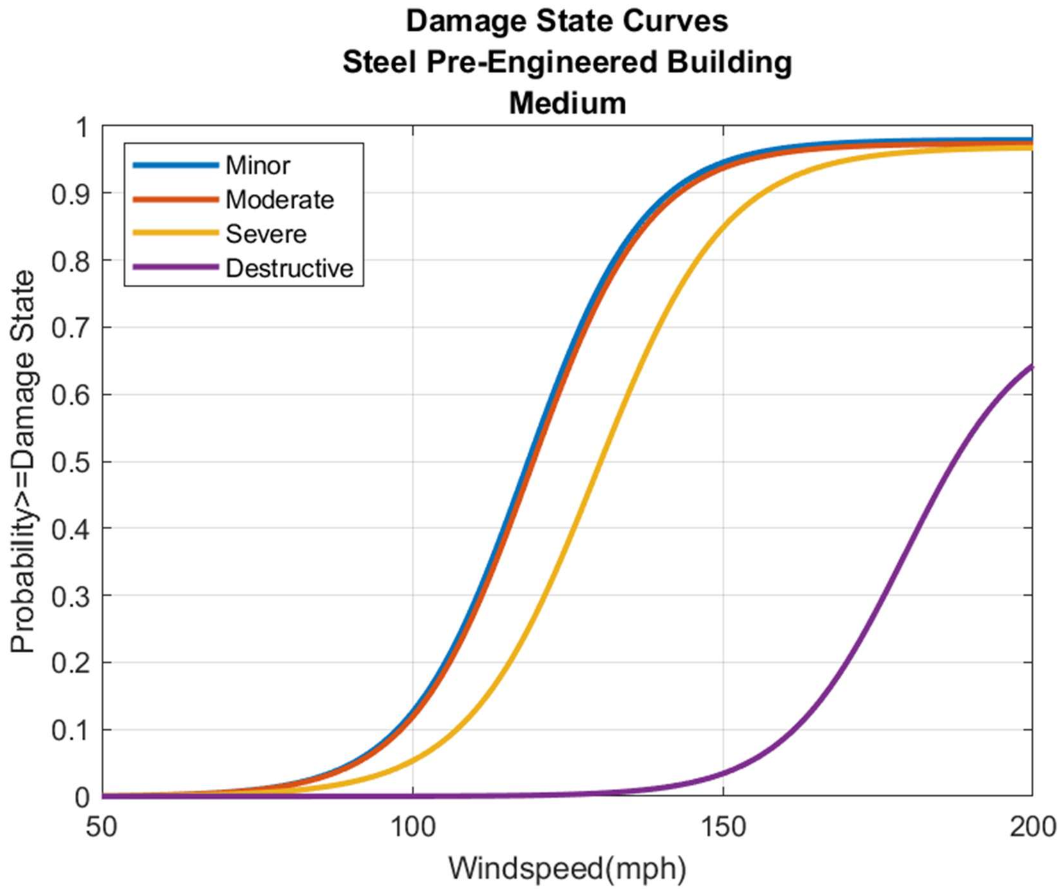

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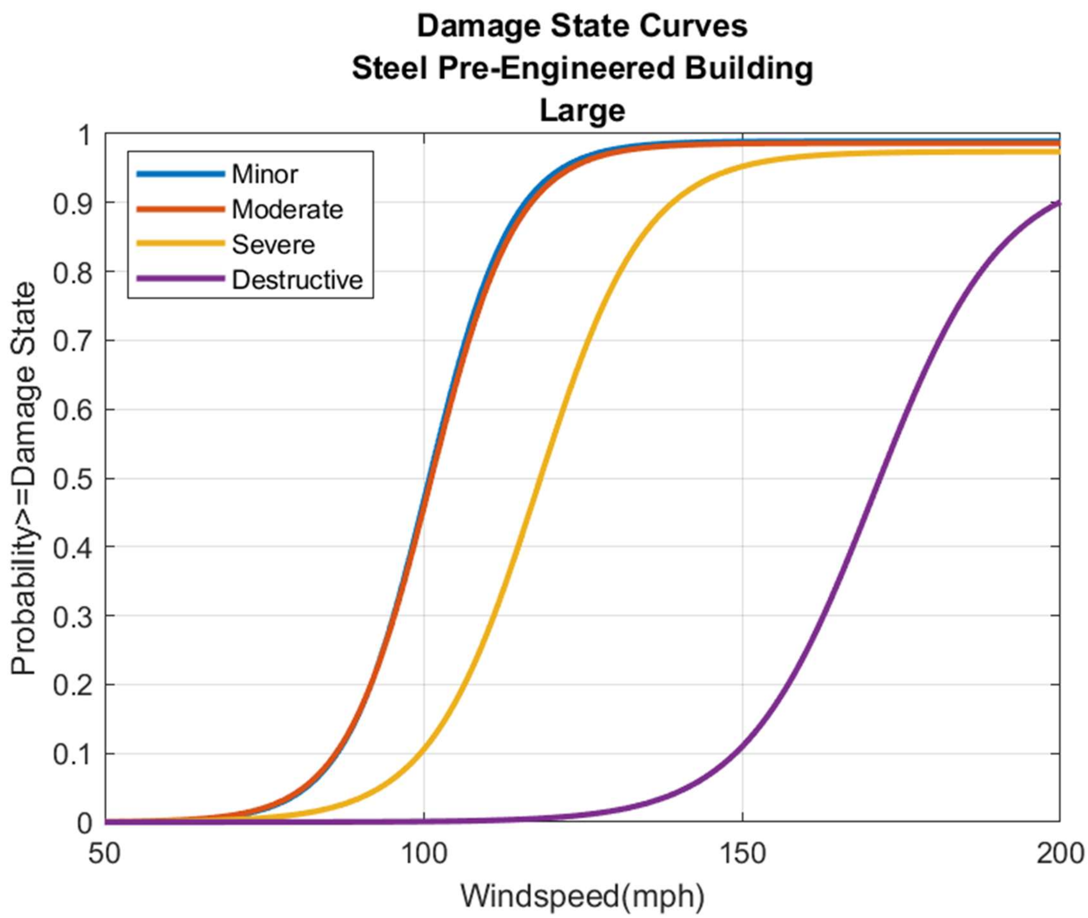

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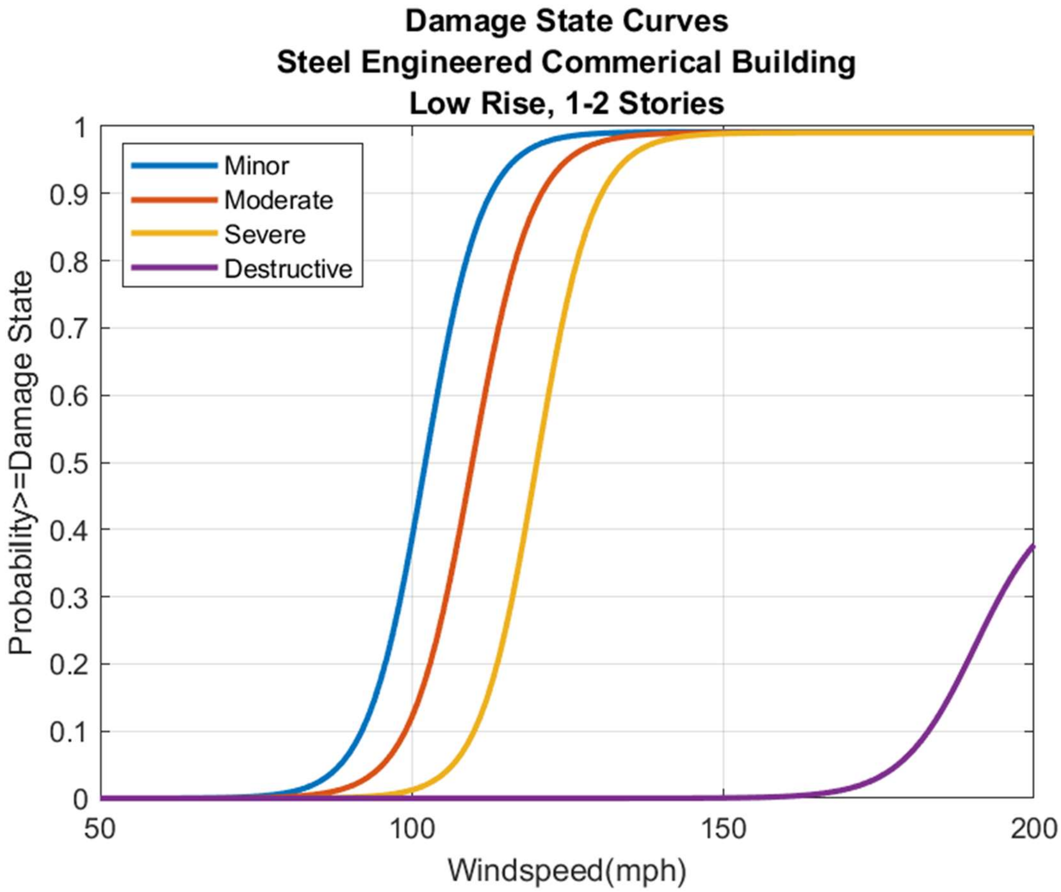

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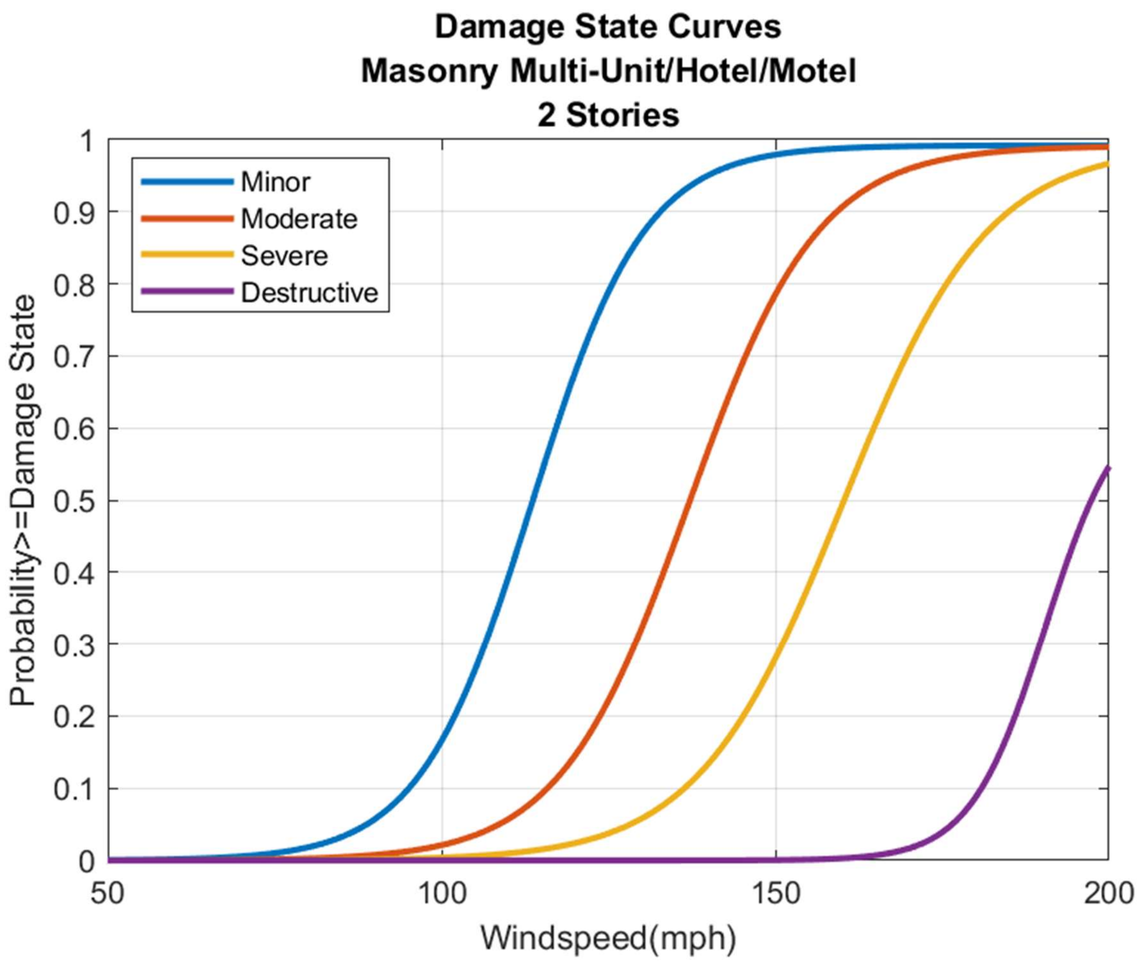

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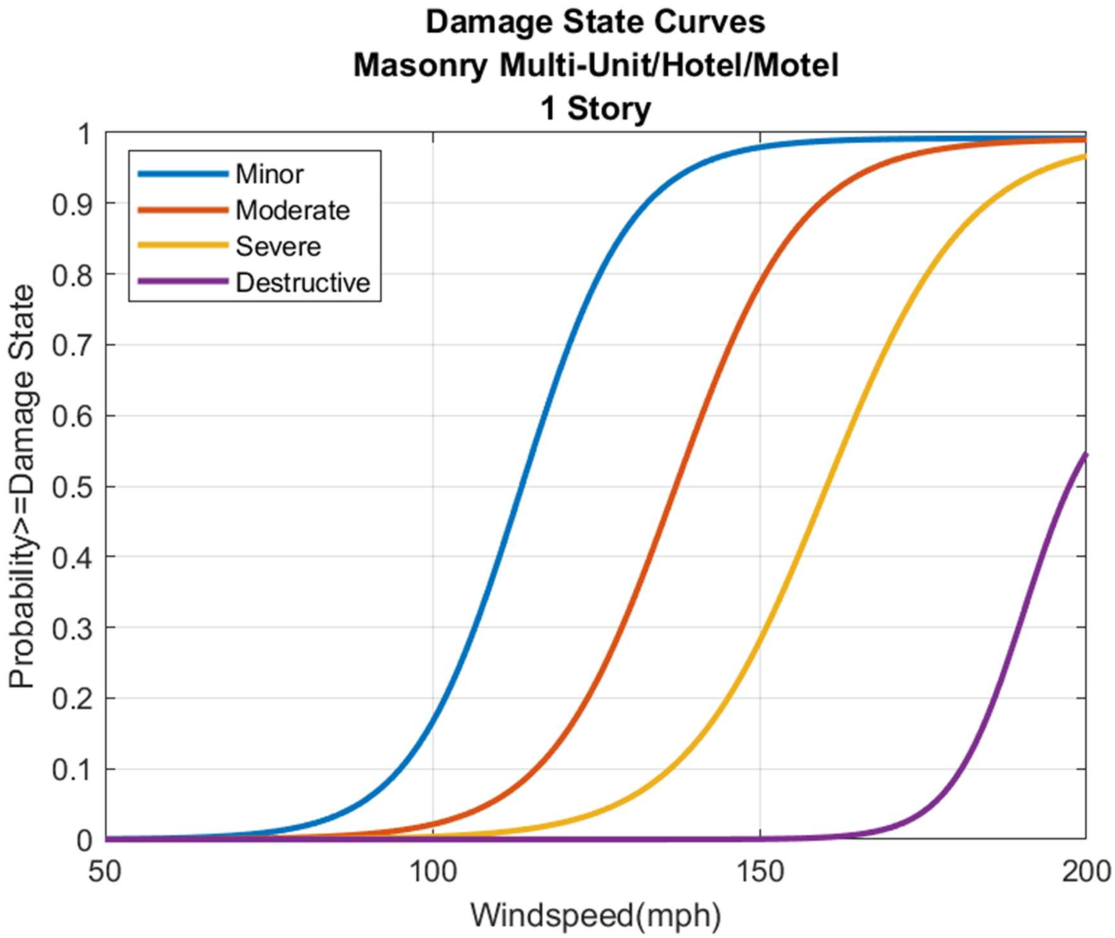

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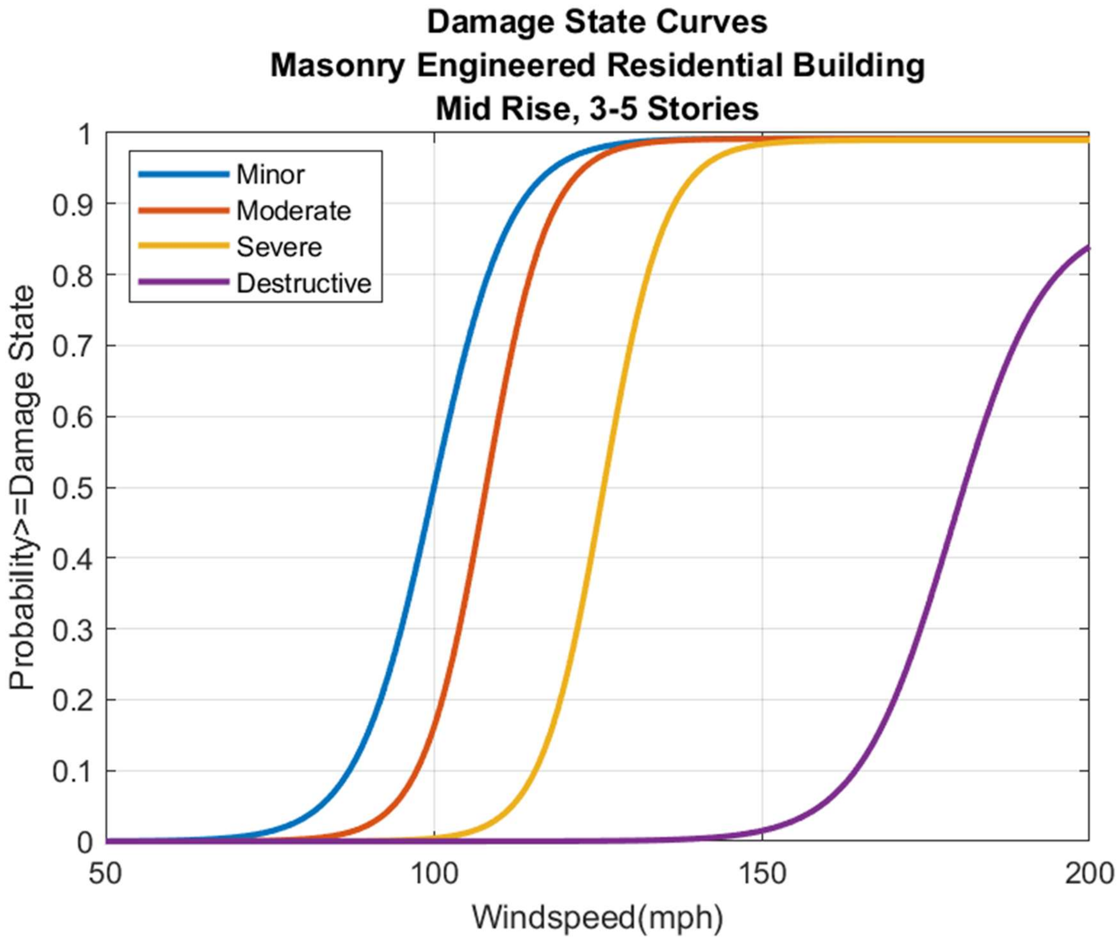

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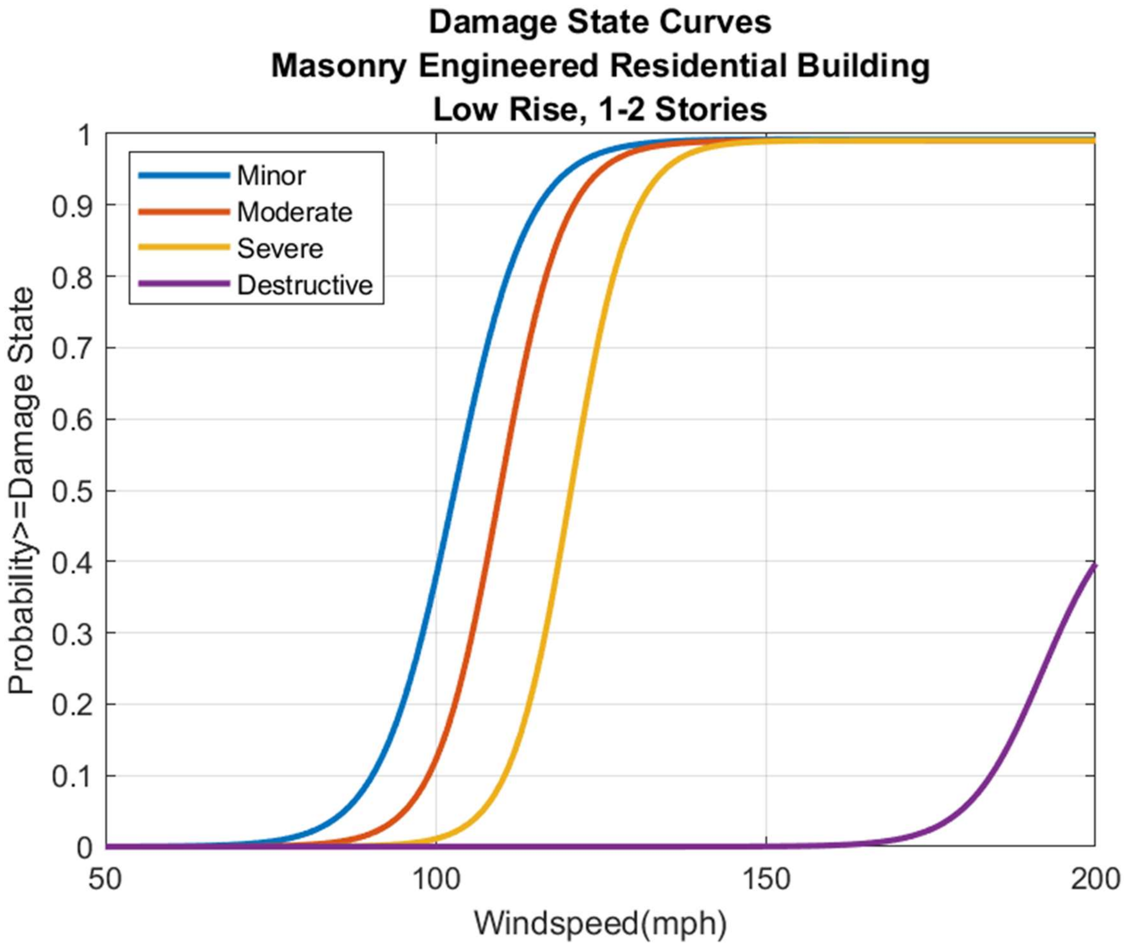

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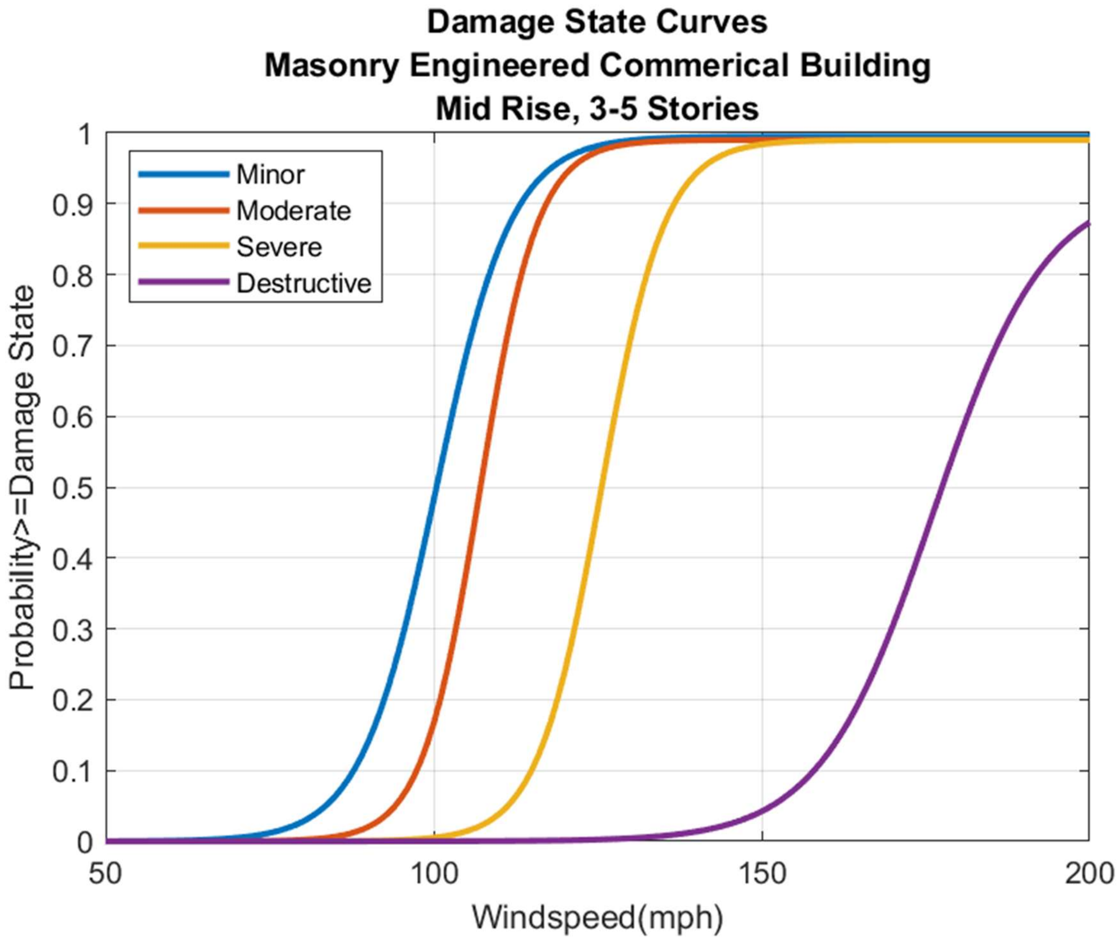
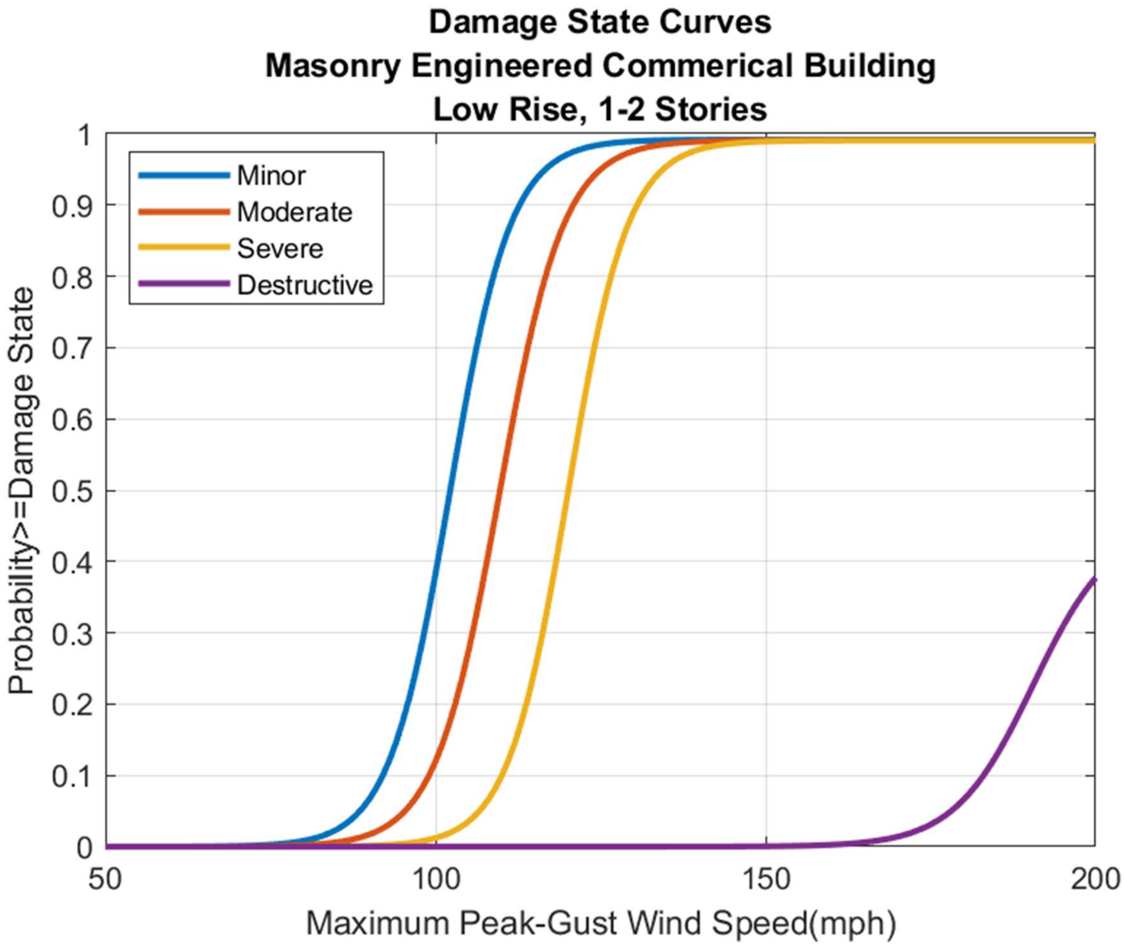


Remodeled damage state curves for SBT MECBM utilizing a fitting logistic curve function within MATLAB Programming for given values Probability>=Damage States and Maximum Peak-Gust Wind Speeds from FEMA HAZUS Hurricane Model TM 2.1.



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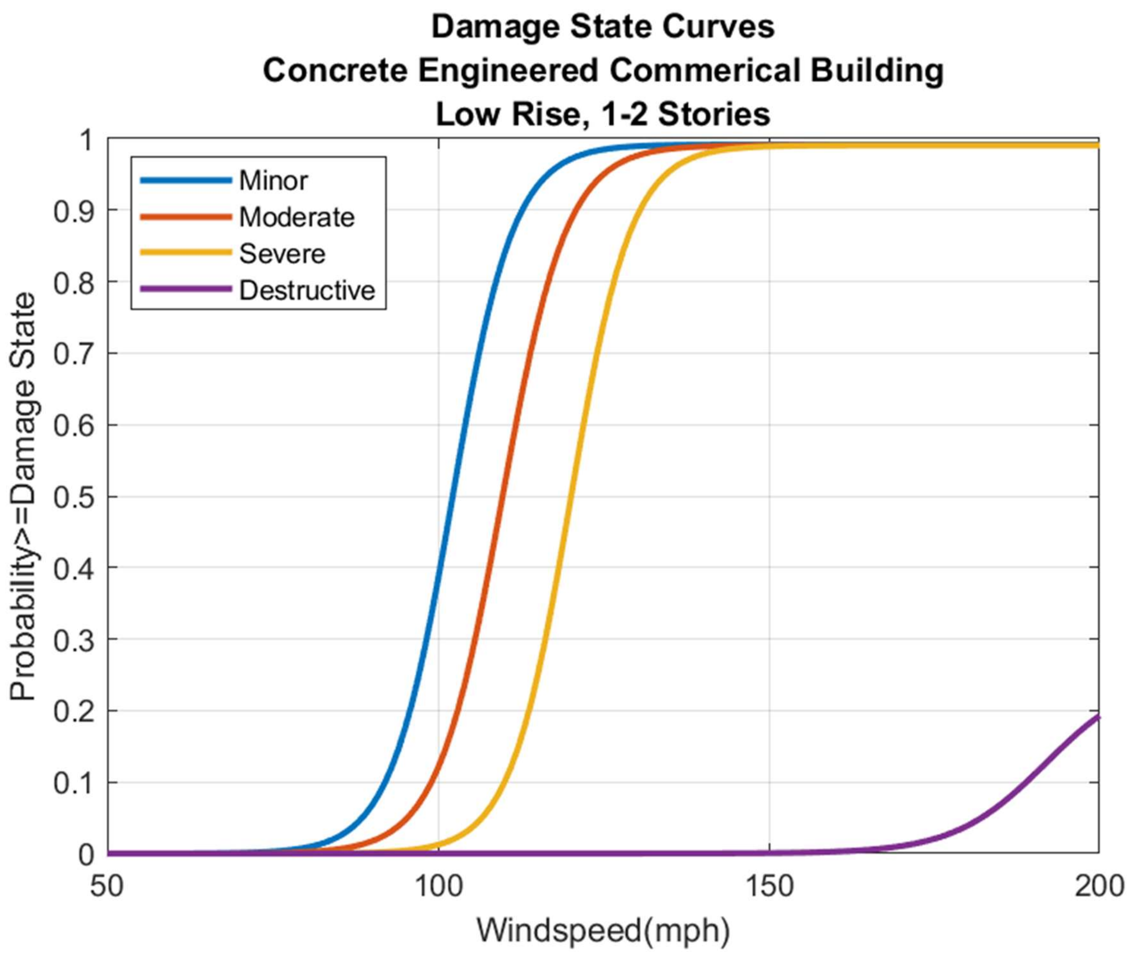


Remodeled damage state curves for SBT CECBL utilizing a fitting logistic curve function within MATLAB Programming for given values Probability>=Damage States and Maximum Peak-Gust Wind Speeds from FEMA HAZUS Hurricane Model TM 2.1.

Appendix E.

Table 6-9. Damage States for Residential Construction Classes

Damage State	Qualitative Damage Description	Roof Cover Failure	Window Door Failures	Roof Deck	Missile Impacts on Walls	Roof Structure Failure	Wall Structure Failure
0	**No Damage or Very Minor Damage** Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof over, with no or very limited water penetration.	≤2%	No	No	No	No	No
1	**Minor Damage** Maximum of one broken window, door or garage door. Moderate roof cover loss that can be covered to prevent additional water entering the building. Marks or dents on walls requiring painting or patching for repair.	>2% and ≤15%	One window, door, or garage door failure	No	<5 impacts	No	No
2	**Moderate Damage** Major roof cover damage, moderate window breakage. Minor roof sheathing failure. Some resulting damage to interior of building from water	>15% and ≤50%	> one and ≤ the larger of 20% & 3	1 to 3 panels	Typically 5 to 10 impacts	No	No
3	**Severe Damage** Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water.	>50%	> the larger of 20% & 3 and ≤50%	>3 and ≤25%	Typically 10 to 20 impacts	No	No
4	**Destruction** Complete roof failure and/or, failure of wall frame. Loss of more than 50% of roof sheathing.	Typically >50%	>50%	>25%	Typically >20 impacts	Yes	Yes

Summarization of facility damage at each damage state level for non-engineered residential buildings; FEMA HAZUS Hurricane Model TM 2.1 (2017)

Table 6-55. Damage States Metal Buildings

Damage State	Qualitative Damage Description	Entry/Over-head Door Failures	Metal Roof Deck Failures	Metal Wall Siding Failures	Missile Impacts on Walls
0	**No Damage or Very Minor Damage** Little or no visible damage from the outside. No broken windows, or failed roof deck. None or very limited water penetration.	No	No	No	No
1	**Minor Damage** Maximum of one broken window or, door or wall panel. Marks or dents on walls requiring painting or patching for repair.	One door	No	One panel	Typically<5 impacts
2	**Moderate Damage** Moderate fenestration failures. Minor roof panel failures, or wall panel failures. Some resulting damage to interior of building from water.	>One to≤33%	One totwo panels	>One to≤15%	Typically5 to 10 impacts
3	**Severe Damage** Major window damage or roof sheathing loss. Extensive damage to the interior from water. Some frame damage likely.	>33% to≤75%	>2 to≤10%	>15% to≤33%	Typically 10 to 20 impacts
4	**Destruction** Significant failures of fenestrations, significant roof and wall panel failures. Significant frame damage likely.	>75%	>10%	>33%	Typically>2 0 impacts

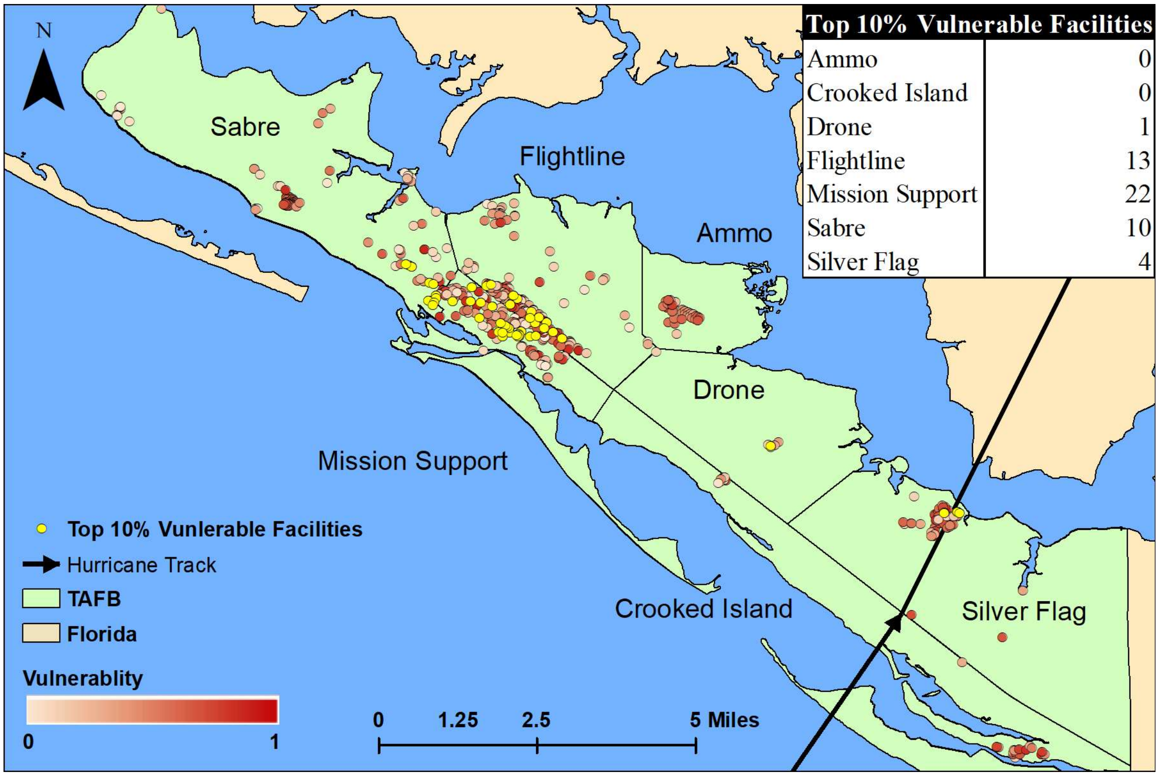
Summarization of facility damage at each damage state level for metal buildings; FEMA HAZUS Hurricane Model TM 2.1 (2017)

Table 6-59. Damage State Definitions for Engineered Steel Buildings

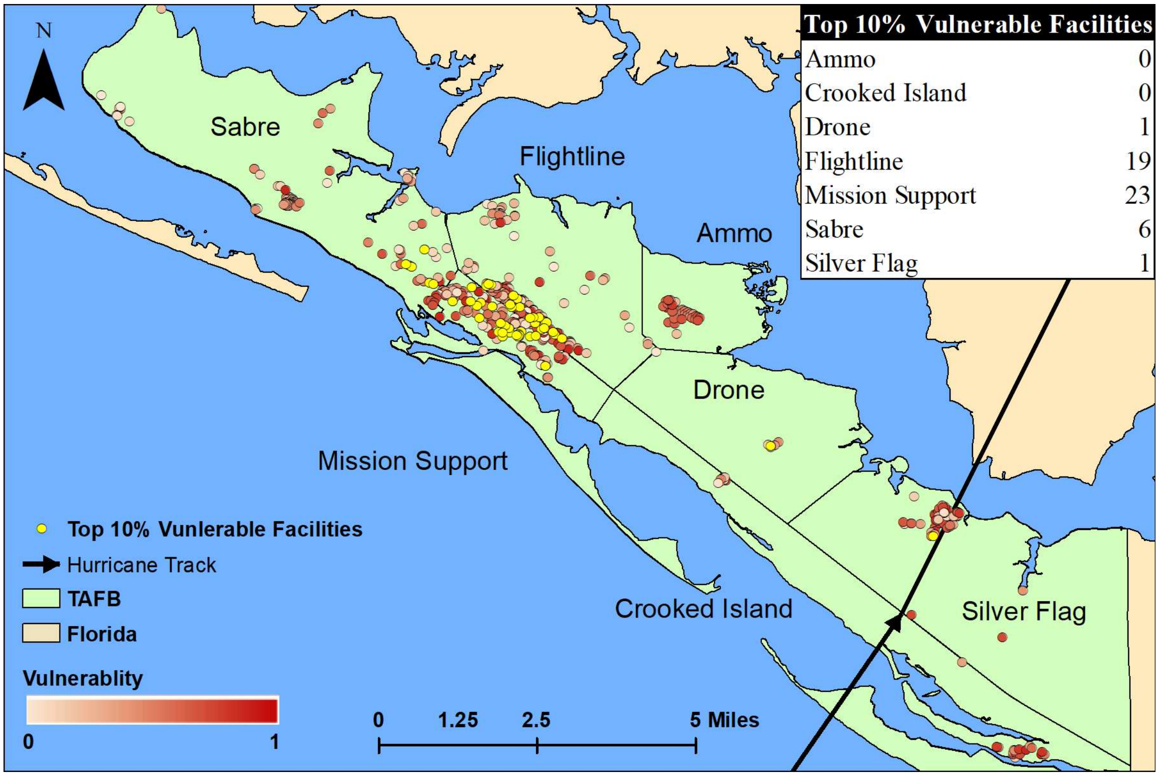
Damage State	Qualitative Damage Description	Roof Cover Failure	Window/ Door Failures	Roof Deck Failure	Missile Impacts on Walls	Joist Failures
0	**No Damage or Very Minor Damage** Little or no visible damage from the outside. No broken windows, or failed roof deck. Minimal loss of roof cover, with no or very limited water penetration.	≤2%	No	No	No	No
1	**Minor Damage** Maximum of one broken window or door. Moderate roof cover loss that can be covered to prevent additional water entering the building. Marks or dents on walls requiring painting or patching for repair.	>2% to≤15%	One window or door	No	Typically <5 impacts	No
2	**Moderate Damage** Major roof cover damage, moderate window breakage. Minor roof deck failure. Some resulting damage to interior of building from water.	>15% to≤50%	>One to ≤2%	One or two panels	Typically 5 to 10 impacts	No
3	**Severe Damage** Major window damage or roof sheathing loss. Major roof cover loss. Extensive damage to interior from water. Limited, local joist failures.	>50%	>2% to ≤25%	>Two to ≤25%	Typically 10 to 20 impacts	One Joist to ≤25%
4	**Destruction** Essentially complete roof failure and/or of more than 25% of roof sheathing. Significant amount of the wall envelope opened through windows failure. Extensive damage to interior	Typicall y >50%	>25%	>25%	Typically >20 impacts	>25%

Summarization of facility damage at each damage state level for engineered residential and commercial buildings; FEMA HAZUS Hurricane Model TM 2.1 (2017)

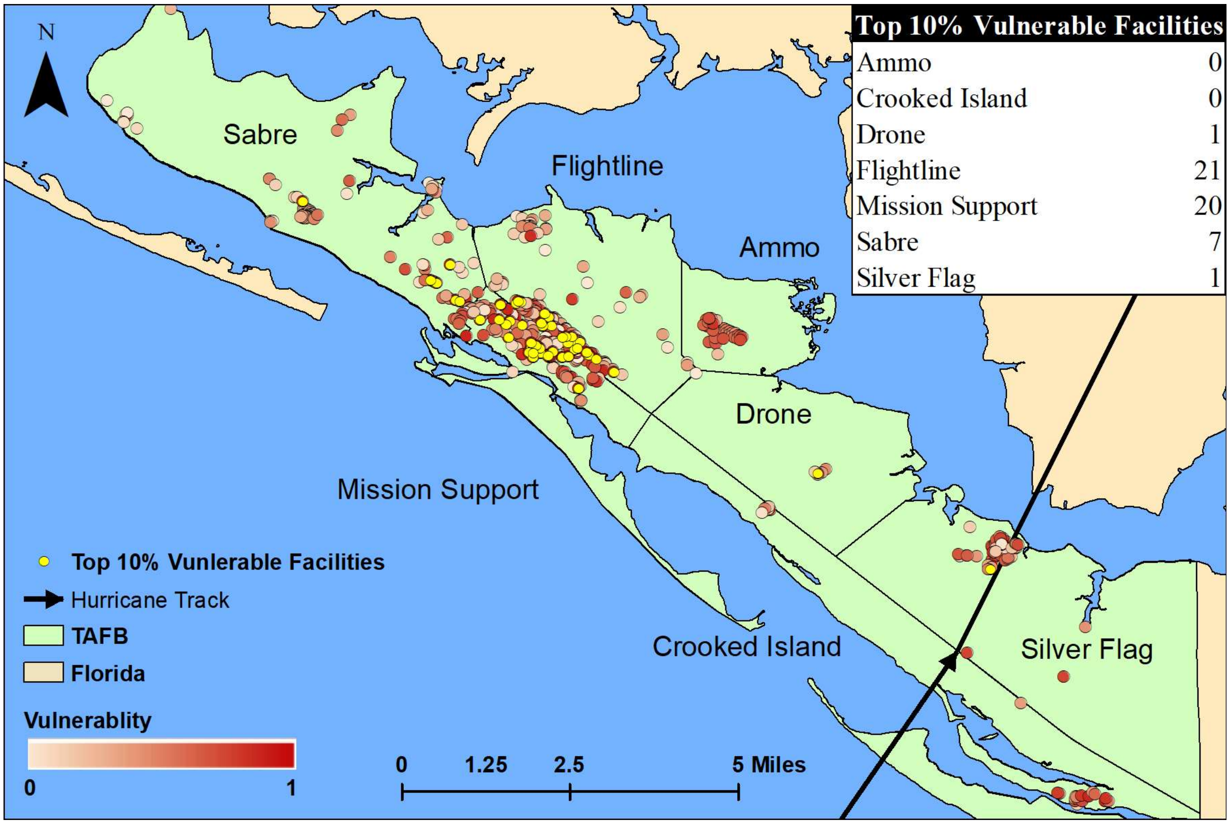
Appendix F.



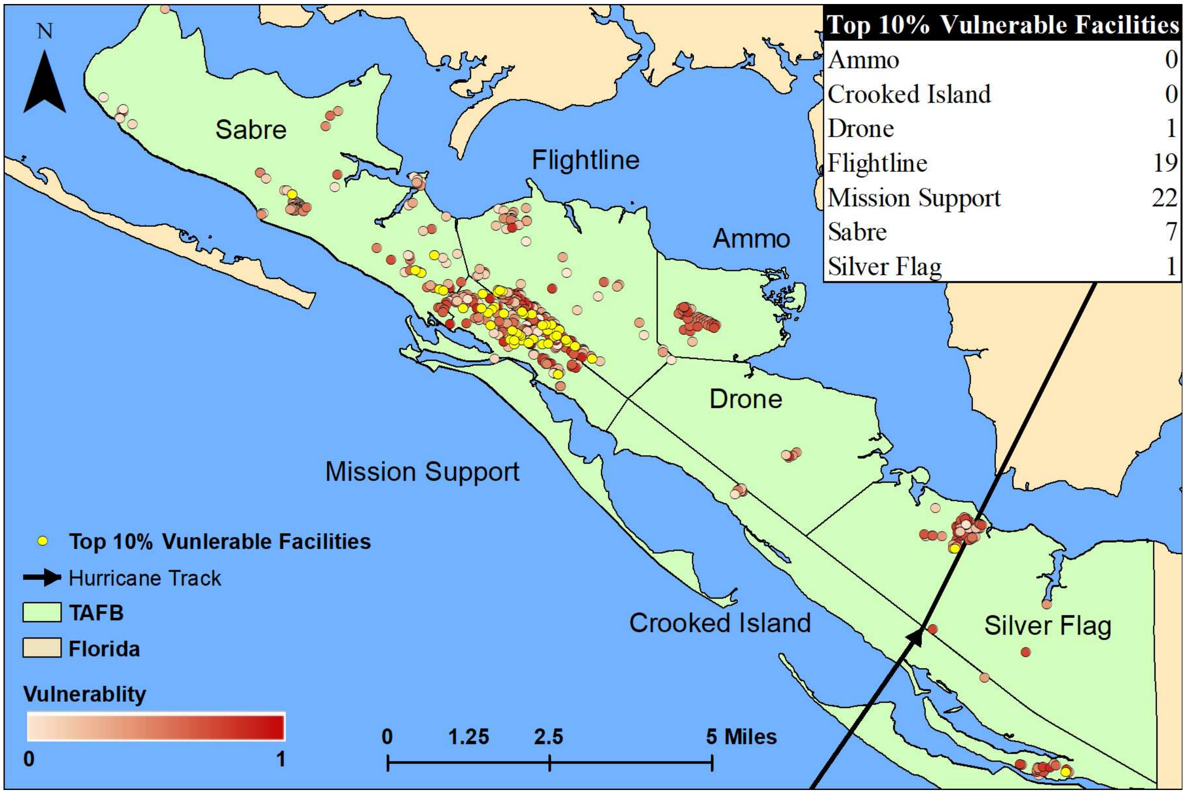
Facility vulnerability map for TAFB during a Category 1 hurricane with 74mph sustained wind speed.



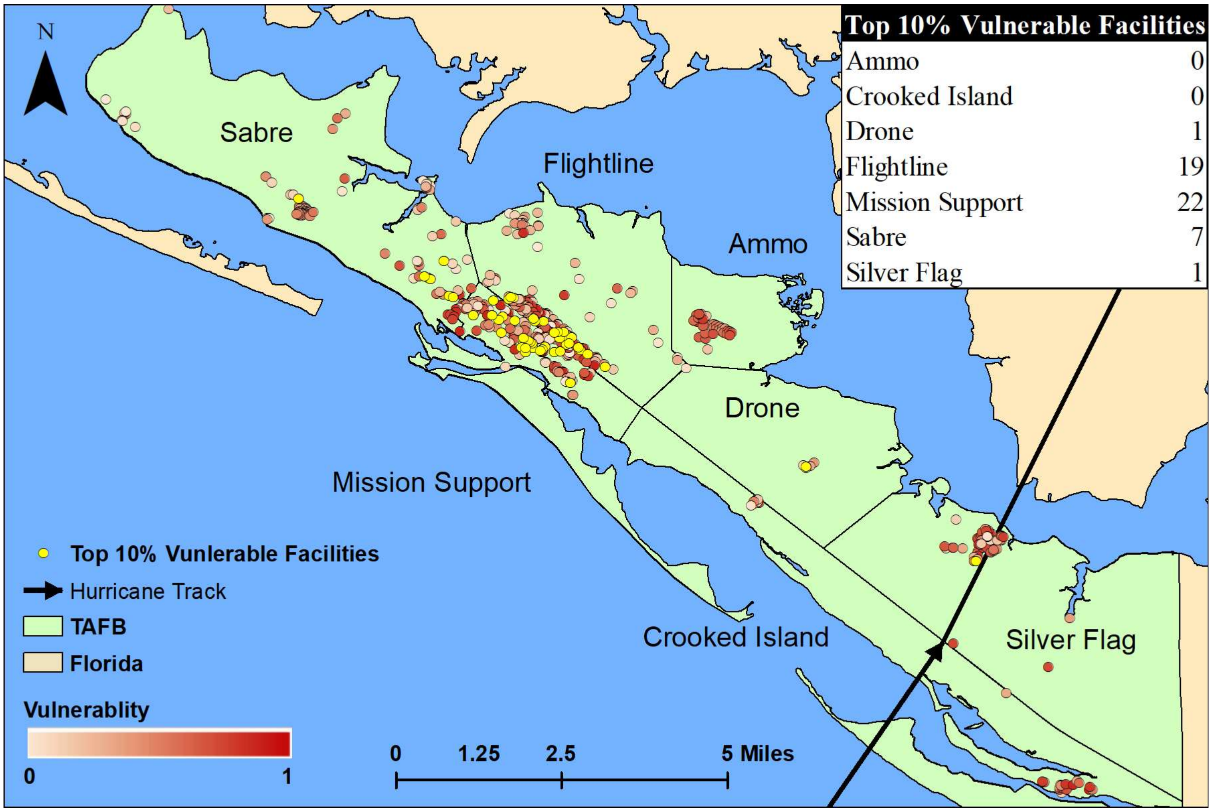
Facility vulnerability map for TAFB during a Category 2 hurricane with 96mph sustained wind speed.



Facility vulnerability map for TAFB during a Category 3 hurricane with 111mph sustained wind speed.



Facility vulnerability map for TAFB during a Category 4 hurricane with 130mph sustained wind speed.



Facility vulnerability map for TAFB during a Category 5 hurricane with 157mph sustained wind speed.

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13. SUPPLEMENTARY NOTES

14. ABSTRACT
Intensifying extreme weather events, tied to the rise in the global average temperature, put global built infrastructure at risk. This presents a daunting challenge for organizational leaders who are tasked to determine how best to adapt current infrastructure to uncertain future events. To develop adaptation plans and policies, vulnerability and risk must be downscaled to an actionable scale, such that planners, designers, and engineers can make adaptation recommendations. However, previous research has largely assessed risk at coarser scales, e.g., regional, national, or global. These assessments are informative, but do not help those tasked to lead adaptation to make detailed, actionable plans. This research focuses on the production of a methodological framework for downscaling extreme event threats to calculate vulnerability and risk at the facility. Using Tyndall Air Force Base (TAFB) as a case study, a building envelope and profile fragility curve-based framework is proposed and tested that uses existing facility attributes to calculate vulnerability to hurricane-force winds. Vulnerabilities are translated to risk using historical return periods for Saffir-Simpson-scale hurricanes. Outputs for Tyndall AFB suggest that risk is highest for Category 2 and 3 storms, and that relative facility vulnerability rankings are stable for Category 3 and larger storms. Generally, this framework provides planners, designers, engineers, and decision makers with the information necessary to determine the extreme-event risk for their facilities such that they may prioritize adaptations, wholistically assess campus-level risk, and determine design events.

15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Lt Col Justin D. Delorit, AFIT/ENV
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