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Defining Resilience, Robustness, and Vulnerability Metrics to Guide Facilities and Infrastructure Decision Making for the United States Air Force

Kelly W. Minor

DEFINING RESILIENCE, ROBUSTNESS, AND VULNERABILITY METRICS TO GUIDE FACILITIES AND INFRASTRUCTURE DECISION MAKING FOR THE UNITED STATES AIR FORCE

THESIS

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Abstract

Tyndall AFB was nearly destroyed after a category five hurricane named Michael tore through the Florida panhandle in 2018. A Program Management Office was stood up to coordinate, plan, and carry out the rebuild efforts of Tyndall AFB. The office's primary responsibility is "building a base capable of supporting a 21st-century mission while also focusing on structural resiliency and efficiency" (Laidlaw 2019). Despite the requirement to build a resilient infrastructure portfolio, the United States Air Force has yet to fully quantify and qualify measures of resilience, including robustness and vulnerability, in the context of their current built infrastructure portfolio. This research defines resilience, robustness, and vulnerability in the context of built infrastructure and proposes an easily accessible taxonomy of metrics to quantify each of these terms. A systematic review of literature explored the public sector's use of resilience, robustness, and vulnerability metrics. Key takeaways include identifying required data inputs for executing the metrics, a generalization of the outputs of each metric, and potential ways for the USAF to leverage each metric with existing SMS data. The resultant metrics identified are then categorized based on the level of analysis used to execute them (campus level, system level, component level metrics). Future endeavors include down-selecting metrics to those most readily implementable by USAF engineers.

Acknowledgments

I want to thank my husband for his support through this journey – I could not have done it without him. To my advisor, thank you for being a great advisor and for motivating me to push through to the end.

Kelly Minor

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1.0 Introduction

In October 2018, Hurricane Michael, a category five hurricane, tore through the panhandle of Florida before making its way up the east coast. Tyndall Air Force Base (Tyndall AFB), located near Panama City, Florida, was decimated. Nearly 300 buildings were damaged or destroyed, and the installation sustained $4.7 billion in total estimated damage (AFIMSC 2018). To handle the level of work required to restore Tyndall AFB, AFIMSC and AFCEC stood up a Program Management Office (PMO) at Tyndall AFB in December of 2018. The PMO's primary responsibilities are to support "building a base capable of supporting a 21st-century mission while also focusing on structural resiliency and efficiency" (Laidlaw 2019). Despite the drive toward a resilient infrastructure portfolio, the United States Air Force (USAF) has yet to fully quantify resilience measures (including robustness and vulnerability) in the context of their current built infrastructure portfolio. To emphasize the scale to which quantifying resilience, robustness, and vulnerability must be applicable, consider that the entire USAF infrastructure portfolio consists of 128,166 facilities—defined as buildings and all supporting infrastructure—which are located at 1,710 sites and have an estimated replacement value of $351.33 billion (Department of Defense 2018).

To accurately provide context for potential measures or metrics of resilience, robustness, and vulnerability, standard definitions are required. These three terms were selected due to the interconnected nature of each. For example, resilience assessments often include vulnerability and robustness assessments as inputs. Woods (2015) stated that resilience could be conceptualized in four ways: resilience as rebound, resilience as robustness, resilience as graceful extensibility, and resilience as sustained adaptability. The primary point in dividing resilience into distinct concepts

allows users to identify what version of resilience they are measuring. Throughout this thesis, resilience is assessed as rebound and graceful extensibility due to the potential for separating robustness and resilience from one another. Robustness is defined hereafter as the ability of a system to withstand damage, either artificial (terrorist attack) or as a result of a natural disaster, without falling into a period of decreased or no functionality (Mishra et al. 2021a). Closely related to resilience and robustness, vulnerability can be defined as the lack of resilience and robustness after an event occurs (Beyza et al. 2019a) or as exposure of an asset to some potentially disruptive event, e.g., a facility exposed to hurricane-force winds. For the purposes of this thesis, vulnerability will conform to the latter definition.

With these definitions in mind, the next step is to inventory metric implementations for each term. Improving infrastructure resilience and robustness while reducing overall vulnerability to disasters is a focus for industry engineers due to the increase in frequency and intensity of climate-related events (Tonmoy et al. 2015). Literature shows that quantification of resilience, robustness, and vulnerability depends on the level of investigation from an asset perspective: component, system, or campus level (Henry and Emmanuel Ramirez-Marquez 2012). Therefore, this review focuses on resilience, robustness, and vulnerability metrics implemented at the component, system, and campus levels and aims to explore the current body of knowledge surrounding these metrics using a systematic literature review process. This review differs from existing reviews in that it organizes metrics by resilience category (resilience, robustness, and vulnerability) and proposes an appropriate level of analysis associated with each metric (campus, system, and component). Ultimately, a taxonomy of these metrics is proposed such that asset managers at all levels can quantify resilience, robustness, and vulnerability within their portfolios

with as much granularity as desired. Managers can then select metrics calculatable based on data they have on-hand or those metrics that can be used across multiple levels of investigation.

1.1 Research Objectives

The objectives of this research are: (1) Identify existing industry use of infrastructure resilience, robustness, and vulnerability metrics through a systematic literature review; (2) propose a taxonomy of these metrics at different levels of implementation: component, facility, and campus levels; and (3) propose recommendations for future adaptations of resilience, robustness, and vulnerability metrics to USAF specific infrastructure applications

1.2 Thesis Organization

This thesis follows a traditional format in which Chapters 2 through 6 systematically build over the subject matter. In Chapter 2, the methodology utilized to conduct the systematic review of literature is detailed. Chapter 3 discusses the bibliometric analysis results from all full-text articles returned from the systematic literature review. The bibliometric data was gathered and analyzed using a combination of SCOPUS and VOSviewer. Chapter 4 presents the results of the literature characterization, including a tabular summary of metric taxonomy, accompanied by a detailed explanation of each metric. Chapter 5 includes analysis and discussion regarding the literature characterization, including commonalities between metrics, potential future suggestions for metric research, the limitations associated with the taxonomy provided, and a discussion of the metrics within the context of USAF infrastructure decision making. Chapter 6 presents general conclusions regarding the research conducted and provides recommendations for aggregating the existing taxonomy to USAF-specific applications.

2.0 Methodology

A systematic literature review was chosen to ensure repeatable investigation of the research space surrounding infrastructure resilience, robustness, and vulnerability metrics. Systematic reviews allow for transparent and comprehensive searches of well-defined research areas. Other researchers can replicate the review process to validate results and address gaps in the research area while acknowledging known and unknowns in the field (Grant and Booth 2009). The widely accepted methodology for conducting a systematic literature review utilizes the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) flowchart and checklist (Moher et al. 2009). Systematic literature reviews start with a specific question to be addressed, which addresses the subject of the study, proposes an action, a comparison of implementing the action to a standard, and the potential outcomes and objectives of the review (Pullin and Stewart 2006). Therefore, the following research question is proposed: "How are industry engineers and researchers quantifying resilience, robustness, and vulnerability in the context of facility infrastructure?" The electronic abstract and article database operated by Elsevier, SCOPUS, was used to obtain all journal articles and conference papers. The remainder of this section outlines the search criteria used to find and evaluate 5,401 journal articles and conference papers and details the exclusion criteria generated to remove irrelevant and duplicate articles, resulting in the 221 articles used in this review.

The central question posed above asks how resilience, robustness, and vulnerability values are calculated across built infrastructure. Four categories organize the search criteria. The basis for the first category is the subject of interest – anything relating to resilience, robustness, and vulnerability needs to be captured using the search criteria. The second category narrows the

application of resilience, robustness, and vulnerability to physical infrastructure and associated synonyms. The third category further narrows the search to the desired action to quantify these terms. Finally, the last category defines the field of resilience, robustness, and vulnerability calculations "to what." In this study, natural and specific artificial disasters are of interest, including weather and climate-related disasters. These four categories are represented in column 1 of Table 1 and are instrumental in selecting the appropriate search terms and placing them in order from the broadest to most restrictive.

Using the pre-defined search criteria shown in Table 1, the authors conducted a database search using three resilience-based terms, three infrastructure terms, three quantification terms, and six application terms. Journal articles and conference papers containing at least one term from each category in either the title, keyword, or abstract appeared in the search results. The "application" terms categorize the application type to prevent premature exclusion if any disaster synonyms were left out. The 5,401 journal articles and conference papers that met the search criteria were downloaded into Zotero to systematize duplicate removal and facilitate screening. Prior to conducting the screening process, 18 duplicate papers were identified and removed, leaving 5,383 articles to consider in the remaining screening process. The remaining screening was conducted in three steps: 1) title-level review, 2) abstract-level review, and 3) full-text review.

Table 1. Systematic Review Search Criteria

Category	Inclusion Terms
Resilience-based	Resilien*, robust*, vulnerab*
Infrastructure	Infrastructure, building, facility
Quantification	Metric, index, measure
Application	terror*, attack, disaster, weather, hazard, climate

The asterisk (*) serves as a catch-all. SCOPUS utilizes Boolean logic, and the asterisk allows for all possible conjugations of associated terms to be included in the search criteria.

The following exclusion criteria removed irrelevant journal articles and conference papers at the title levels: 1) all non-infrastructure applications, including medical and social sciences, 2) all cyber-based infrastructure applications. Most records removed resulted from the infrastructure term "building" and the quantification term "measure." When used as a verb, "building" was often implemented in edifying social or community resilience/robustness instead of the noun form, which coincided with infrastructure topics. The term "measure" often implied policy-level implementations of resilience that did not produce quantifiable metrics associated with built infrastructure. The exclusion criteria resulted in removing 4,667 records, leaving 716 to move from the title level to the abstract level.

At the abstract level, 716 records entered the screening process. At this level, records that did not quantify either resilience, robustness, or vulnerability and did not articulate applicability to physical infrastructure were removed. 326 articles were removed, yielding 390 articles to be evaluated based on a full-text review. At the full-text level, 390 articles entered the screening process. Many articles evaluated theoretical or futuristic technologies, specifically in the computer science and engineering domains, that currently do not exist within the public sector, much less

the DoD. Excluded articles include those that only evaluated resilience, robustness, and vulnerability using modeling software without explicitly defining metrics or measures used within their analysis or if their analysis did not calculate infrastructure resilience, either operationally or physically. For example, many articles assessed social resilience after a disaster by addressing only socio-economic factors and omitting infrastructure, which does not meet the research question intent. 169 articles were removed at this stage, leaving the 221 eligible records included in this systematic review. Figure 1 summarizes this process in the PRISMA flowchart.

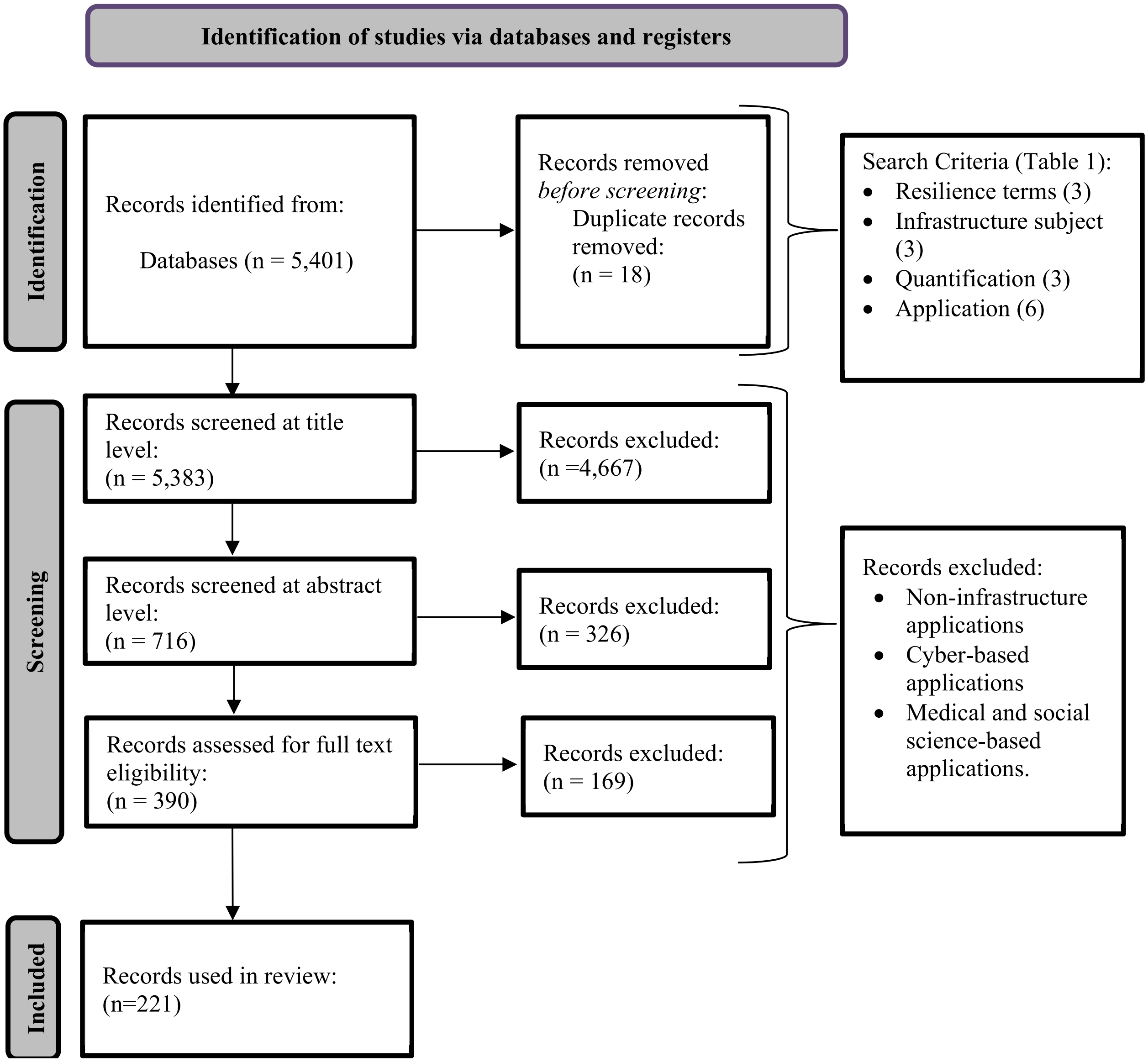

Figure 1. PRISMA Flowchart summarizing this systematic review from 5,401 results to 221 over three screening levels.

3.0 Bibliometric Analysis

After conducting the systematic review of literature described in the previous section, the 221 remaining articles were processed through VOSviewer and SCOPUS bibliometric software. The results of this include time-series and location publication analyses, co-authorship analysis, keyword co-occurrence identification, and an h-index calculation.

Figure 2 shows the progression of resilience, robustness, and vulnerability publications included in this review between 2004 and June 2021. The number of papers published between 2004 and 2013 increased consistently through 2021. However, the trend has been generally positive and appears exponential by observation. Since 2018, publications have sharply increased, which suggests that the field related to resilience, robustness, and vulnerability metrics has gained the research community's attention and has provided the basis for continued novel applications of these metrics. Based on the inclusion and exclusion criteria, the earliest year papers were included in this review was 2004. The drop in 2021 publications is due to the review being conducted only through June of 2021.

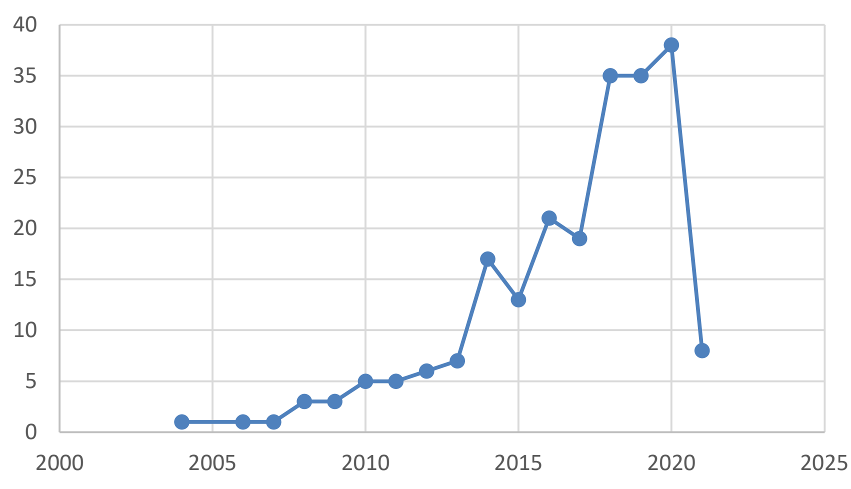

Figure 2. Annual Publication Count

Figure **3** shows the top 10 countries by publication count in infrastructure resilience, robustness, and vulnerability metrics. The United States is the top producing country, with 99 publications. The domination of the United States in this field of research is due to the active engagement of the Office of the President through Presidential Policy Directive 21, which places the responsibility of defining and assuring infrastructure resilience in the hands of both public and private sector entities, from the federal to local levels (Office of the Press Secretary 2013).

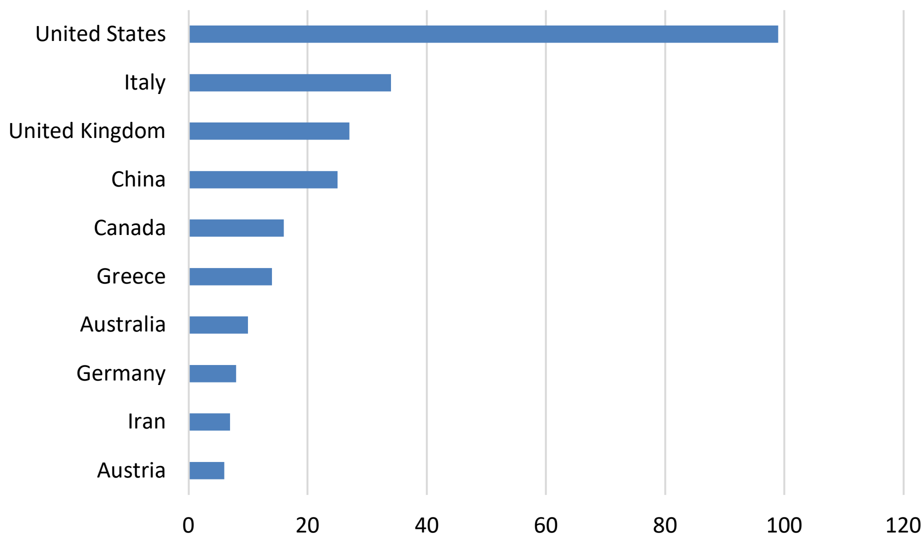

Figure 3. Count of Publications by top 10 Countries

Co-authorship analysis contains three distinct elements: circle size (count), color (relationship), and line connections (co-occurrences). The results of this analysis are shown in Figure 4. Circles are specific to each author; a more significant size equates to more publications. Circle and line color indicate distinct author clustering. Cluster size was set to 3 publications, with no minimum number of citations specified. The distance and line thickness between authors

indicates the number of co-publications (a smaller distance equates to higher co-occurrences). Top producing authors are Cimellaro G, Reinhorn A, and Bruneau M, each comprising one main cluster.

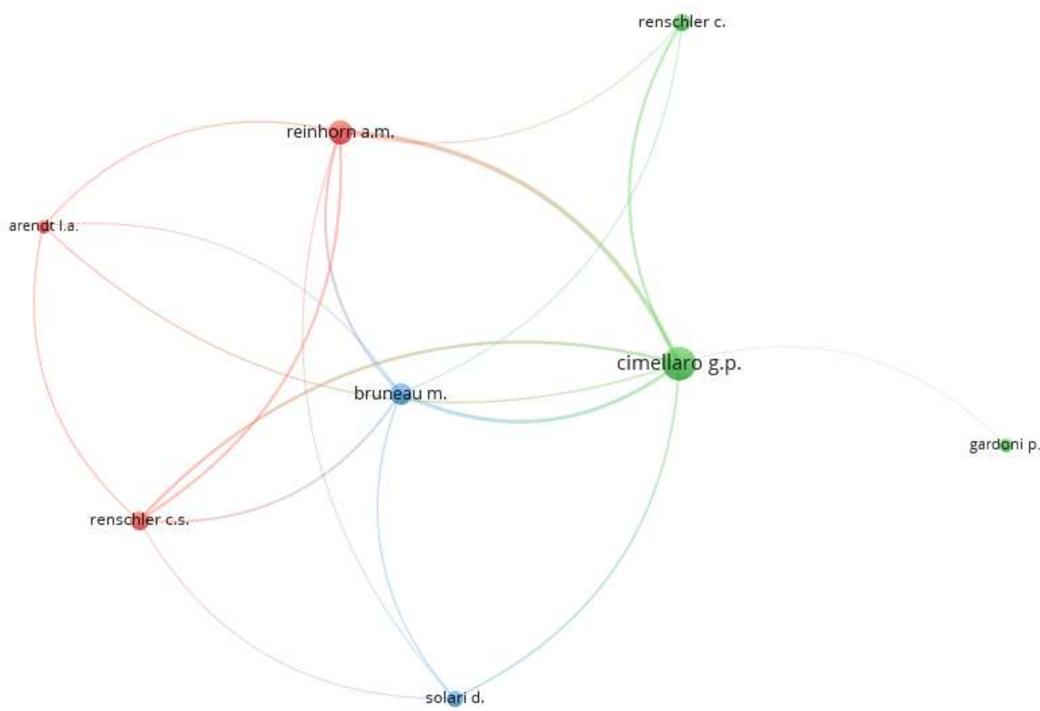

Figure 4. Author-Co-Occurrences

A keyword co-occurrence analysis was generated to explore the connections between the articles used in this review and validate that no major subjects were omitted in the search string terms. Like the author's analysis, circle size indicates word use frequency, line weight, and distance represent the number of co-occurrences of each word, and color indicates clusters. Figure 5 shows the result of the keyword occurrence analysis. The colors in Figure 5 are independent of those in Figure 4. The top three words linking all publications used in this review are resilience, risk assessment, and disaster. Four clusters are present, with at least ten occurrences of each word.

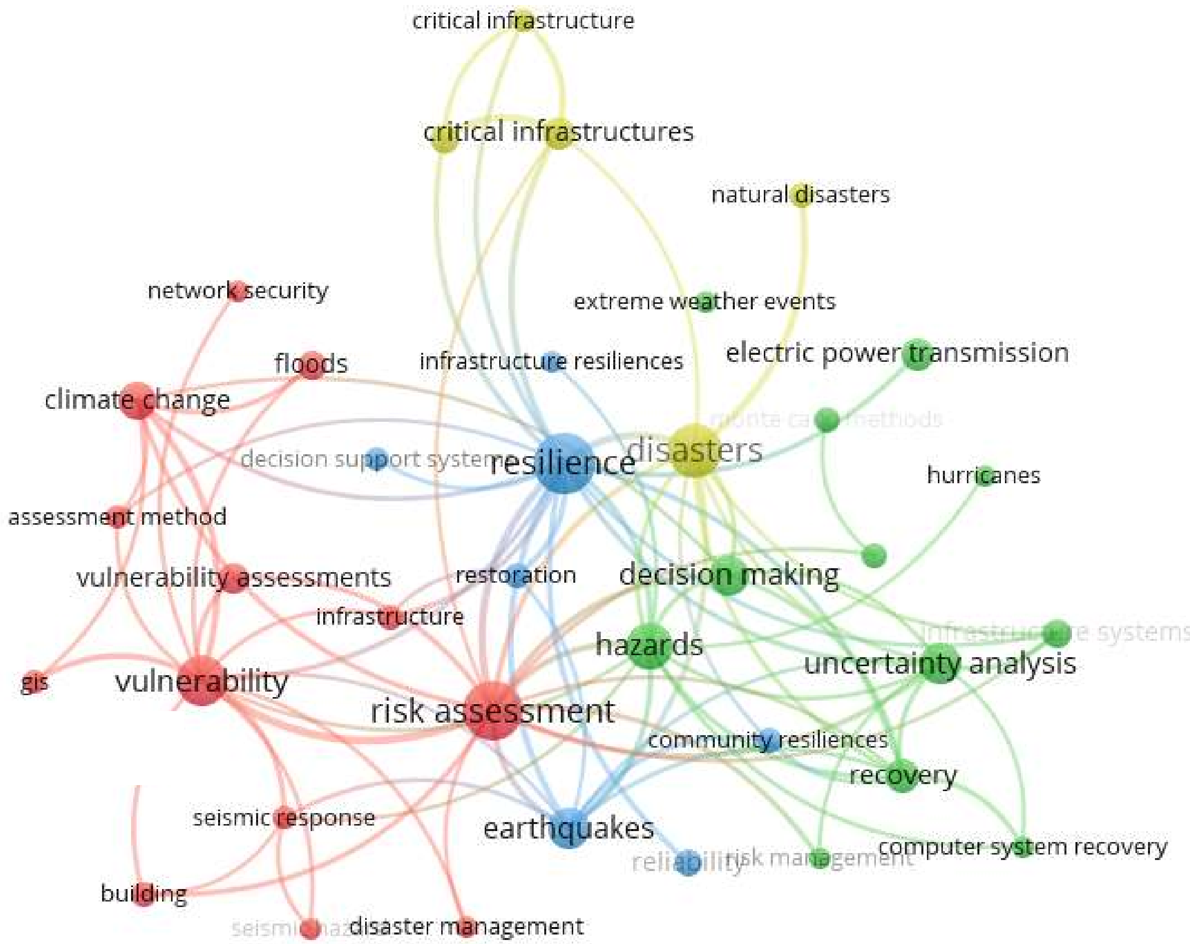

Figure 5. Keyword Co-Occurrences

An h-index evaluates productivity in publication at the author level and the citation impact of those publications. The h-index is the maximum number of articles an author has published with at least as many citations (Sarli 2021). The papers used in this review have an h-index of 39 (Figure **6**), with a total of 503 citations for the most cited publication, Francis and Bekera 2014.

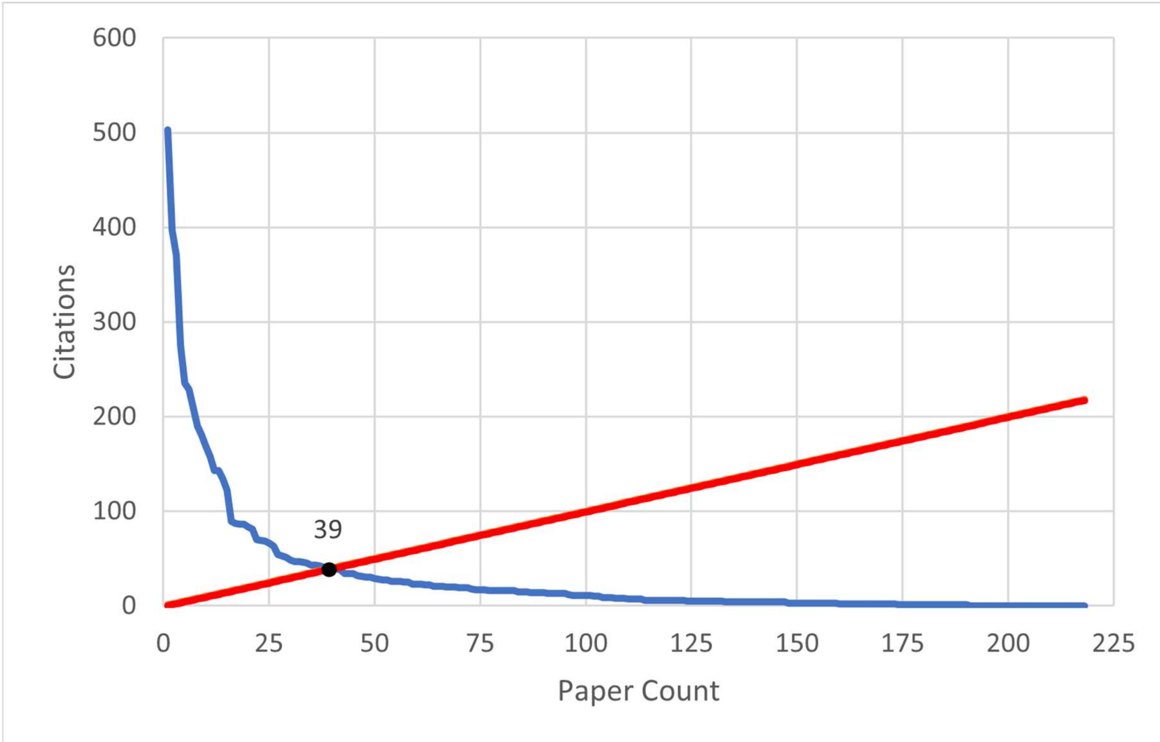

Figure 6. H-Index calculated as the maximum number of publications by an author with at least as many citations.

Table 2 contains the ten most cited publications. Figure 7 shows the results of the citation analyses conducted over the papers included in this review by publication type. The resulting publications comprised 61% peer-reviewed journal articles, 34.4% conference papers, 4.1% review papers, and 0.5% book chapters. The journal articles spanned 11 subject areas, including engineering (37.6%), earth and planetary sciences (15.3%), and environmental sciences (10.6%).

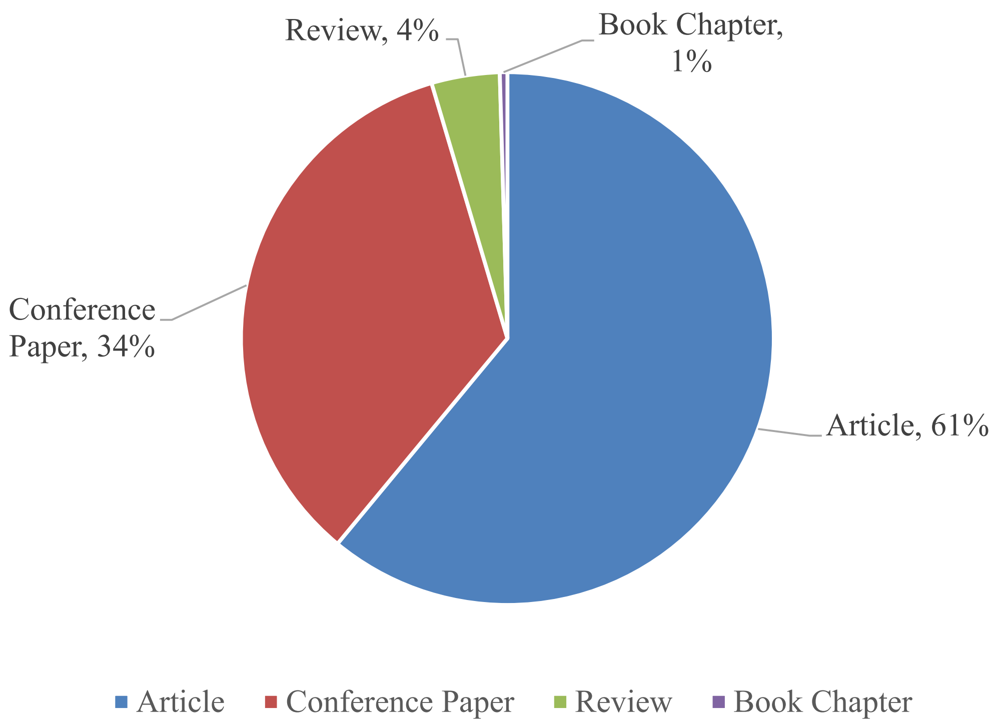

Figure 7. Publication by Type

Table 2. Highest cited articles used in the systematic review

No.	Year	Journal Title	Document Title	Type	Times Cited
1	2014	Reliability Engineering and System Safety	A metric and frameworks for resilience analysis of engineered and infrastructure systems	Review	503
2	2012	Structural Safety	A three-stage resilience analysis framework for urban infrastructure systems	Article	397
3	2004	Earthquake Spectra	Measuring improvements in the disaster resilience of communities	Article	370
4	2009	IEEE Systems Journal	Methodology for assessing the resilience of networked infrastructure	Article	275
5	2010	Chaos	Do topological models provide good information about electricity infrastructure vulnerability?	Article	235
6	2013	Reliability Engineering and System Safety	Resilience-based network component importance measures	Article	229
7	2015	Journal of Infrastructure Systems	Measuring the performance of transportation infrastructure systems in disasters: A comprehensive review	Review	209
8	2017	IEEE Transactions on Power Systems	Metrics and Quantification of Operational and Infrastructure Resilience in Power Systems	Article	190
9	2017	IEEE Transactions on Power Systems	Power System Resilience to Extreme Weather: Fragility Modeling, Probabilistic Impact Assessment, and Adaptation Measures	Article	180
10	2017	Reliability Engineering and System Safety	A quantitative method for assessing resilience of interdependent infrastructures	Article	168

4.0 Literature Characterization

After completing the systematic literature review, the articles were organized by category (resilience, robustness, or vulnerability), then by level of analysis (campus, system, component). Campus-level articles include those applied at the community scale to be comparable to an Air Force Installation, as a whole. System-level articles include those applied across one or more infrastructure systems. For example, articles that analyzed electrical distribution/generation systems and those that analyzed standalone facilities comprising multiple infrastructures such as electrical and mechanical systems were both considered system-level articles. Component-level articles include specific assemblies of a more extensive system or the structural and functional materials. For example, an article defining a bridge as part of a more extensive transportation system or analyzing the bridge's structural materials were considered component-level articles. After the articles were organized by level of analysis, specific metrics were identified within each article. Table 3 summarizes this process. In the category column, the number in the denominator represents the 221 articles resulting from the systematic literature review, and the numerator represents the number of articles that apply to the specific category. It is important to note that a single article could be applicable to any number of the three categories. The metric column identifies the specific metric utilized in the article and displays the number of articles within the category that the metric was present. The level of analysis columns displays the applicability of the metric to a specific level of analysis, and the number of relevant articles at each level.

Table 3: Taxonomy of Resilience, Robustness, and Vulnerability Metrics*

Category	Metric	Level of Analysis		
		Campus	System	Component
4.1 Vulnerability (105/221)	Vulnerability Index (44/105)	23/44	15/44	6/44
	Fragility Curve (45/105)	14/29	25/29	6/29
	Network Analysis (16/105)	6/16	10/16	N/A
4.2 Robustness (24/221)	Network Analysis (15/24)	7/15	8/15	N/A
	Robustness Index (9/24)	N/A	4/9	5/9
4.3 Resilience (131/221)	Resilience Curve (66/131)	36/66	51/66	15/66
	Resilience Index (58/131)	35/58	41/58	11/58
	Network Analysis (28/131)	19/28	22/28	N/A

*A 10% threshold was established for each metric to consolidate results, meaning that the number of articles related to a metric at a specific level of analysis must account for at least 10% of the total articles found for the specific category and level of analysis.

The following sections detail each metric identified in Table 3 including the required inputs, expected outputs, and identification of appropriate levels of analysis. Vulnerability is displayed first as it was the easiest category to separate from resilience, followed by robustness. Network analysis is incompatible at the component level because nodal inputs are required for the analysis, which is the component level scale defined by this paper. Section 4.1 covers vulnerability metrics, section 4.2 covers robustness metrics, and section 4.3 covers resilience metrics. Each section presents examples and associated sources.

4.1 Vulnerability Metrics

Vulnerability, typically quantified through vulnerability assessments, captures the inherent weaknesses unique to a type of built infrastructure (Argyroudis et al. 2020b). These assessments are derived using empirical or analytic evidence, expert opinion, or hybrid methods (The World Bank Group 2019). In general, the calculation of vulnerability metrics varies based on the hazard type, meaning that the calculation of a vulnerability metric tied to hurricanes, for example, will differ from a metric calculated for tornados (Ismail et al. 2012). For example, an area subject to a hurricane is likely to be exposed to widespread storm surge and severe winds, while an area exposed to a tornado is not exposed to storm surge but to, local severe winds. The most common metrics identified through this systematic literature review are vulnerability indices, fragility curves, and the use of network analysis. Section 4.1.1 identifies and explains the use of vulnerability indices. Section 4.1.2 identifies and explains the use of fragility curves. Section 4.1.3 identifies and explains the use of network analysis. Each discussion includes the inputs required to conduct the analysis, the expected outputs, and a brief passage on the levels of analysis the metric was used (campus, system, and component level).

4.1.1 Vulnerability Index

Three input dimensions are required to calculate a vulnerability index: 1) the scale of analysis, 2) the hazard, and 3) the appropriate input parameters to evaluate based on the hazard and desired scale of analysis. The resultant vulnerability index is calculated from these inputs by evaluating and weighing each input parameter. The selection of input parameters is accomplished through stakeholder engagement, empirical data selection using principal component analysis (Malgwi et al. 2020), or expert judgment based on previous studies (Sheik Mujabar and

Chandrasekar 2013). The weights associated with input parameters are often derived leveraging multi-criteria decision analysis (Tonmoy et al. 2015) or analytical hierarchy process (Alam et al. 2012). An example of a campus-level assessment is presented by Ismail et al. (2012), which evaluates a coastal tsunami vulnerability index. The authors divided the quantification of an infrastructure vulnerability index into three sections, which define the input parameters: 1) building vulnerability, dependent on the physical characteristics of the built infrastructure, 2) degree of protection provided for a building, and 3) the recorded flood depth at a building. Equation 1 displays this framework:

$$SV = Bv \times D_{prot} \times FD \tag{1}$$

where SV is structural vulnerability and drives the scale of analysis; Bv is the building vulnerability; D_{prot} is the degree of protection provided to the building based on natural and built obstacles; and FD is the measured flood depth. Each is evaluated on a multi-point Likert scale, e.g. 5-point.

Bv, D_{prot}, and FD represent the required input parameters to evaluate the structural vulnerability of buildings to flooding due to a tsunami. SV sets the desired scale of analysis, while Bv, FD, and D_{prot} bound the index parameters to infrastructure parameters unique to tsunami flooding. To further clarify tsunami flooding relevant input parameters, Ismail et al. (2012) defined Equation 2:

$$Bv = w_1 a + w_2 b + w_3 c + w_4 d + w_5 e + w_6 f + w_7 g \tag{2}$$

where w_i is a weighted factor, a is the number of stories in a building; b represents the material used to construct the building; c represents the hydrodynamics of the ground-floor; d represents the type of building foundation; e represents the number of movable objects; f represents the

orientation and shape of the building; and *g* represents the condition of the building. Input parameters *a* through *g* were evaluated on a 5-point Likert scale, further explained in Ismail et al. 2012.

While this example is specific to flooding caused by a tsunami, the basic input and output requirements hold for any hazard, so long as the appropriate hazard and scale of analysis are identified. Through the systematic review of literature, vulnerability indices were found to be scalable from the campus level to the system level and from the system level to the component level.

Campus-Level Applications

Evaluating a vulnerability index at the campus level requires the appropriate scaling of all input parameters and parameter categories in addition to infrastructure. These categories often include environmental factors (Tonmoy et al. 2015), socio-economic factors (Lam et al. 2014, Kantamaneni 2016, Cunningham et al. 2021), and local political factors (Lam et al. 2014a). Equations 1 and 2, as evaluated by Ismail et al. 2012, were calculated at the building level or system level. They only considered the impacts to infrastructure, aggregated to the building scale. Lam et al. 2014 demonstrate the scaled inputs and additional parameters required to conduct a campus-level assessment, due to hurricane exposure using a vulnerability index. The authors consider population density, socio-economic status of the local population, road and communication network densities, and recorded damage in US dollars as weighted input parameters in their calculation of a community (campus) level vulnerability index, as shown in Equation 3:

$$V = 0.2(HZ) + 0.2(PD) + 0.6(1 - AC) \qquad (3)$$

where V is the campus level vulnerability index; HZ is the hurricane recurrence factor; PD is the weighted sum of the local population density and the percent of the population living below 6 meters in elevation; and AC is the local adaptive capacity, defined as a weighted sum of socio-economic inputs (including income inequality and percent of the population below the poverty line), technological factors (including electricity consumption), and infrastructure inputs (including road density and telephone access). The additional considerations given to socio-economic and technological inputs make this analysis a campus-level assessment using a vulnerability index .

System-Level Applications

System-level vulnerability indices are only concerned with the impacts to the infrastructure category of vulnerability. Therefore, the input parameters are only applicable to a specific type of infrastructure subject to a specific hazard. Azarm et al. 2018 demonstrates the generation of a system-level vulnerability index of a bridge subject to an earthquake. The authors use Equation 4 to generate vulnerability indices for various bridges in a more extensive transportation network:

$$SVI = V_{struct} \times F_{hazard} \times F_{site} \quad (4)$$

Where SVI is the structural vulnerability index of the bridge; V_{struct} is a weighted combination of structural characteristics of bridges selected from prior research; F_{hazard} is a seismic hazard index calculated using peak ground acceleration (PGA); and F_{site} is a weighted combination of locally driven factors, such as liquefaction. This equation differs from Equation 3 in that it only considers the impacts of the hazard to the bridge infrastructure itself and does not include any consideration for non-infrastructure-related factors, such as socio-economics. This difference is what defines a system-level vulnerability index.

Additional general system-level input parameters are described in Kemp (2007). Other hazards and infrastructure-specific examples include a building's vulnerability to tsunamis (Honesti et al. 2015a), transportation systems subject to hurricanes (Mhatre et al. 2018), and power systems subject to terrorist attacks (Wang et al. 2017b).

Component-Level Applications

It is important to note that there is some debate about the definition of a component-level vulnerability assessment, which complicates evaluating a vulnerability index at this level. This is shown by comparing Azarm et al.(2018), who considered a bridge a standalone system, comprised of a series of structural components, with Argyroudis et al. (2020), who defined a bridge as a component of a more extensive transportation system. The structural elements comprising the bridge in Azarm et al. (2018), and the bridge as a component of the more extensive transportation system in Argyroudis et al. (2020), are considered component-level analyses, with the connection being a clear establishment of system/component boundaries prior to analysis. Component-level vulnerability indices are similar in structure to system-level indices, in that they only reference a specific type of infrastructure subject to a specific hazard. However, the input parameters are evaluated on a finer scale.

4.1.2 Fragility Curves

Fragility curves are graphical displays of multiple, probabilistic, damage-state fragility functions calculated over a range of intensity measures, as shown in Figure 8. The value of these curves is in ease of interpretability; a two-dimensional relationship between probability and intensity measure, the output of which is a single exceedance probability value for an associated intensity measure and damage state.

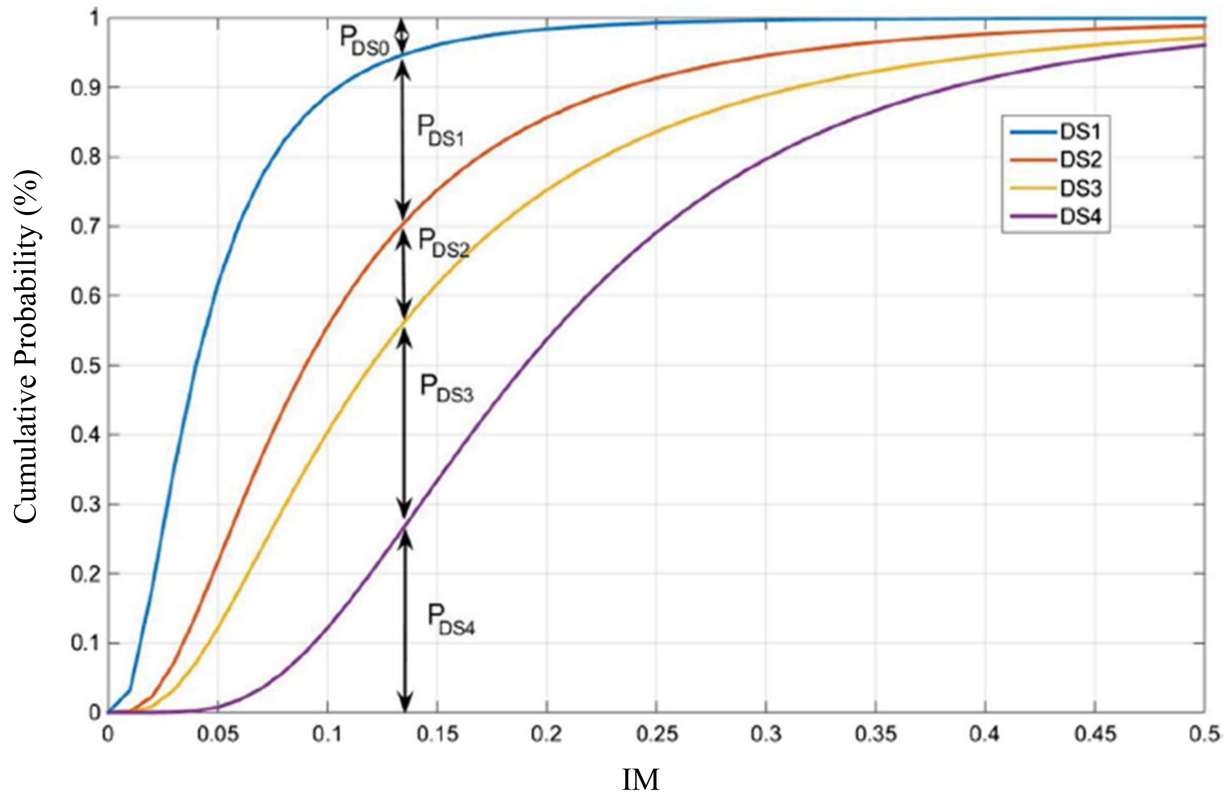

Figure 8: Sample Fragility Curve adapted from Kilanitis and Sextos 2019

Two inputs are required to produce a fragility curve: 1) The intensity measures unique to the hazard, and 2) fragility functions unique to the component/system/campus in question evaluated over the range of intensity measures. Intensity measures are hazard-dependent event intensities, such as peak ground acceleration (PGA) associated with earthquakes (Argyroudis et al. 2020b), or wind speeds associated with severe wind events (Panteli et al. 2017b). Fragility functions calculate the probability of an object subject to damage that exceeds pre-defined damage states across hazard intensity levels (Kilanitis and Sextos 2019a).

These functions take the basic form shown in Equation 5, adapted from Porter et al. 2007:

$$P(D|IM = x) = \Phi\left(\frac{ln\left(\frac{x}{\theta}\right)}{\beta}\right) \quad (5)$$

where *P(D|IM)* is the conditional probability that the object of interest will be damaged, at a minimum, to a specified damage state at a given intensity measure, *IM*; where ϕ is a cumulative distribution function; x is the intensity measure value of interest; where θ represents the median value of the probability distribution; and β represents the standard deviation. These fragility functions often utilize log-normal cumulative distributions because they fit a wide range of structural and non-structural applications, supported by years of research (Porter et al. 2007). However, more flexible distributions, e.g., Gamma and Weibull are also appropriate given their ability to approximate many distributions.

The functions themselves are derived in multiple ways, including analytical derivation—calculating the median and standard deviation parameters from raw event data; selection of pre-defined functions from large databases such as HAZUS (United States Federal Emergency Management Agency 1969); and standard empirical derivation processes (Porter et al. 2007). Fragility curves are calculated at the component and system levels, then aggregated by system characteristics to generate a campus-level assessment.

Campus-Level Applications

Campus-level use of fragility curve is dependent upon the system-level evaluation of the fragility curve, typically over some characteristic of the system (typically building material composition (Bozza et al. 2017), or structural typology (Aguilar-Meléndez et al. 2019a), which is then applied to a portfolio of similar infrastructure to obtain a campus-level vulnerability

assessment. An example of this is presented in Aguilar-Meléndez et al. (2019), where the authors aggregate fragility of buildings in Barcelona, Spain, across two categories, based on structural typology. Fragility curves were generated for each typology, then applied to the buildings in the city of Barcelona, resulting in a district-level seismic vulnerability exceedance probability value for each building typology, across five specified damage states.

System-Level Applications

System-level fragility curves are generated by selecting the appropriate fragility functions associated with the system of interest, and evaluating them over the appropriate hazard intensity measures for various damage states (Tsinidis et al. 2019a). Physical characteristics of the system aggregate these curves and associated functions. For example, HAZUS—a multi-threat spatial damage analysis tool—defines fragility curves for 16 building types, including light-frame wood, mobile homes, concrete shear walls, 7 transportation systems, including ports and highways, and 6 utility systems, including potable water and communications (FEMA 2020). Each facility is assigned damage state descriptions, fragility function inputs, and an associated distribution (commonly lognormal or Poisson), based on earthquake-specific intensity measures. Intensity measures are hazard-dependent. Standard intensity measures for specific hazards include peak ground acceleration (PGA) and peak ground velocity (PGV) for earthquakes (Tsinidis et al. 2019a), wind speed for wind-related events (Panteli and Mancarella 2015a), and rain intensity for hurricanes (Panteli and Mancarella 2015a). Examples of fragility curves generated by system type include power transmission systems subject to high winds (Panteli et al. 2017b), buildings subject to landslides after an earthquake (Bozza et al. 2017), and bridge systems subject to flood conditions (Mitoulis et al. 2019a).

Component-Level Applications

Component-level fragility curves are evaluated over the individual components that underly a larger system. An example of this is provided in the Hazus technical manual, in appendix A-16, where a power generation facility (system) is broken into 8 component types, including boilers, pumps, and valves, with each assigned a damage state and fragility function parameters to evaluate over peak ground acceleration intensities during an earthquake (FEMA 2020). These inputs can be evaluated using Equation 5 to generate fragility curves for each component of the power generation system. Additional component-level fragility curve examples include bridges, overpasses, and tunnels evaluated over PGA intensities (Kilanitis and Sextos 2019a), and generators, tie switches, and hardened power lines evaluated over wind speed intensities (Mukherjee et al. 2020a).

4.1.3 Network Analysis

In the context of infrastructure vulnerability analysis, network analysis is used to model the network (system or systems), using links and nodes to delineate critical features (Bozza et al. 2017). Once the network has been modeled, the vulnerability of specific nodes and links can be assessed using performance criteria unique to network analysis, including measures of connectivity, path length and flow (Starita et al. 2018a), by removing nodes and links in the network. Connectivity and path length metrics evaluate network topology, while flow-based metrics define the network performance based on network type (number of passengers transitioning through train stations, as an example) (Li et al. 2020). The method of removal to accurately represent the hazard the network is exposed to is essential. For example, Li et al. (2020) simulate a terrorist attack on a network by mathematically deriving node and link attack strategies

that mimic the coordination and randomness associated with terrorist attacks. The inputs and expected outputs of using network analysis depend on the performance criterion of interest. However, all require pre-and post-disruption information about the network, and the difference in performance is the magnitude of the vulnerability.

Connectivity-driven metrics are focused on individual nodes in the network. The only inputs required to use these metrics in a vulnerability assessment are the identification and count of nodes and links associated with the network (system) of interest, and the directionality of the network. Connectivity-driven metrics include determining node degree and network accessibility. Node degree is the number of links (connections) incident to a given node, which helps determine the criticality of the node to the larger network, calculated using a simple summation of all connections to a node (Starita et al. 2018a). Network accessibility quantifies the connectivity of nodes after a disruption occurs in the network that removes or damages existing connections and is modeled by Equation 6 (Starita et al. 2018a):

$$NA = \frac{1}{n(n-1)} \sum_{i=1}^{n} n^{i}_{disrupted} \tag{6}$$

where NA is the network accessibility; n is the number of nodes in the network; $n^{i}_{disrupted}$ is the number of nodes that can be reached from node i, after disruption. The inputs required to calculate this are the number of nodes and the directionality of the network.

Path-length driven metrics are based on assessing efficiency through the network, and require knowledge about path length and network directionality (Starita et al. 2018a). An example of path-length is the distance between train stations measured in miles in a rail network, while directionality refers to whether a train can only travel in one direction between stations or not.

Starita et al. 2018 describe three metrics to assess path-length vulnerability metrics: 1) network topological efficiency, 2) node vulnerability, and 3) node betweenness. Network efficiency assumes path-length and efficiency are inversely proportional and is therefore calculated as shown in Equation 7 (Starita et al. 2018a):

$$E = \frac{1}{n(n-1)} \sum_{s,d=1}^{n} \frac{1}{SP_{sd}} \tag{7}$$

where E is the efficiency of the entire network; n is the number of nodes in the network; and SP_{sd} is the shortest path connecting node s to node d. The inputs required to use this metric are the number of nodes in the network, their associated lengths, and the directionality of the network. Node vulnerability is the evaluation of the impact of a node on network efficiency after it is removed from the network, as shown in Equation 8 (Starita et al. 2018a):

$$NV = E(i) = E(O) - E'(i) \tag{8}$$

where NV is the node vulnerability of the network; $E(O)$ is the network efficiency calculated before removing node i; and $E'(i)$ is the network efficiency calculated after removing node i. The inputs required to use this metric are the same as for Equation 7, just re-calculated post-disruption. Node betweenness counts the number of times a node is part of the shortest path through the entire network. Betweenness centrality is calculated using node or edge betweenness to determine how influential a node/link is to connecting other nodes and links (Kermanshah et al. 2017a). Betweenness centrality is calculated using Equation 9:

$$C_B(n_i) = \sum_{jk} \frac{n_{jk}(i)}{n_{jk}} \tag{9}$$

where $n_{jk}(i)$ is the number of shortest paths linking nodes *j* and *k* through node *i,* and n_{jk} is the total number of shortest paths linking nodes *j* and *k.* The inputs required to calculate betweenness include path-lengths, network directionality, and the nodes and links associated with each path through the network (Starita et al. 2018a).

Flow-driven metrics are unique to the network they describe and are based on the quantity of system information traveling to and from nodes through the links (Li et al. 2020). An example of this is comparing the number of passengers traveling through certain train stations before and after a node or link is disrupted (Sun et al. 2015). Network analysis can be used to conduct vulnerability analyses at the campus and system levels.

Campus-Level Applications

Campus-level vulnerability-based network analyses combine topological and flow metrics and evaluate holistic network performance pre and post disruption. Topological metrics correctly graph the network, while flow metrics represent the performance evaluator. At this level, vulnerability is assessed as the impact on network flow performance after nodes are systematically removed, simulating a hazard. An example of this was conducted by Li et al. (2020) where they modeled a city as a combination of interdependent systems in a single network, including water, power, and heating/cooling. They evaluated a flow-based vulnerability metric before and after network disruptions. To simplify the problem, they defined their boundaries as the power and water systems, modeling them as one network with one failure mode being a loss of a power node or link and another failure mode as the loss of a water node or link. Topological measures of connectivity and node degree define the directionality and accessibility of the network. They then removed nodes and links one at a time throughout the network and evaluated flow through the

network before and after removal before repeating the process by removing multiple nodes and links simultaneously. The flow-based metric used to evaluate network performance uses a summation of weighted maximum flow ratios through each interconnected system through time, for the non-disrupted and disrupted states. By doing this, they identified the most vulnerable nodes in the network and optimized flow through the network based on a variety of disruptions.

Additional examples of campus-level analyses include the assessment of traffic flow interruptions in a major US city due to flash-flooding (Kermanshah et al. 2017a) and comparing the flow of people and goods through a city before and after a significant earthquake (Bozza et al. 2017).

System-Level Applications

System-level use of network analysis looks at one system at a time, evaluating vulnerability using each type of metric (connectivity, path length, and flow) separately, rather than combining them, as in a campus-level analysis (Kermanshah et al. 2017a). Kermanshah et al. (2017) demonstrate this by evaluating the vulnerability of a road network to flash-flooding. The authors define vulnerability in two dimensions: 1) static, whereby they only consider measures of connectivity and path-length, including node degree and node betweenness, and 2) dynamic, whereby they only consider flow through the road network, including the number of trips the road network sees pre-disruption versus post and the number of interrupted trips the disruption caused. For the static metrics, specifically node betweenness, the authors state that the higher the betweenness centrality, the more vulnerable the network is due to the likelihood of heavier traffic disruption (Kermanshah et al. 2017a). For the dynamic metrics, the disruption in traffic flow is assessed as a ratio of pre-and post-disruption trips completed. The authors make this assessment

using two distinct ratios. The first is the percentage of trips that could not be completed due to a node being isolated (meaning associated links were removed due to flooding). The second is the percentage of total trips affected inside the flash flood impact area. The authors state that the road network is more vulnerable to flash flooding when these ratios are higher (Kermanshah et al. 2017a).

Additional examples of system-level use of network analysis include a power distribution system subject to random attacks (Zio et al. 2008a) and floodgates subject to changes in hydrological infrastructure (Ogie et al. 2016).

4.2 Robustness Metrics

Robustness metrics seek to quantify the ability of an element to resist damage or disruption or to prevent cascading failure throughout a system (Biondini 2009). These metrics inherently rely on some degree of damage capacity of the component, system, or campus, so the calculation of robustness metrics varies based on the physical characteristics of the component, system, or campus (Ribeiro et al. 2013). As an example, a bridge subject to flood inundation will perform differently than a 2-story house subject to the same degree of flood inundation. The most common metrics identified through this systematic literature review are robustness indices and network analysis. Each metric is presented with the inputs required to conduct the analysis, the expected outputs, then a brief discussion of the levels of analysis the metric was used (campus, system, and/or component level). Section 4.2.1 identifies and explains the use of network analysis. Section 4.2.2 identifies and explains the use of robustness indices.

4.2.1 Network Analysis

In the context of robustness, network analysis metrics predominately evaluate either node or link robustness subject to different failure modes (Wang et al. 2019a). The characteristics of the network involved drive the network topography, while the failure mode (random or targeted (including spatially localized failure, which attempts to represent cascading system failures) is driven by the hazard the network is exposed to (Wang et al. 2019a). Random failures describe most natural disasters, while targeted failures focus on the nodes and links in a network that are most important to network functionality and often describe terrorist attacks (Wang et al. 2019a). Measures of connectivity, including node degree, path length, and betweenness (see Equation 9), are evaluated across nodes and links in the network prior to a disruptive event and are directly

compared to the same calculations conducted post-disruption (Yazdani and Jeffrey 2012, Dong et al. 2019).

The inputs required to use these network analysis metrics require proper topological representation of the network (correct placement of nodes, directionality considerations to travel through the network, and length of paths through the network) and an accurate failure mode to represent the hazard the network is exposed to. A practical example of this is the airport network in Canada where individual airports are identified as nodes, and all flyable routes between airports are links. The path length defines the distance between airports (km) or travel time (min), and the directionality is established as undirected because planes can fly both to and from all airports in the network. Failure modes include random and targeted attacks (Yassien et al. 2020). The expected output using this method evaluates what aspects of the network experienced performance loss due to a specific type of failure. If an area performed at the same level pre-and post-disruption, it is considered robust. A drop in performance would indicate a lack of robustness (Wang et al. 2019a). Equation 10, adapted from Wang et al. (2019a), demonstrates this as a ratio of pre-and post-disruption performance:

$$V_p = \frac{P_{norm} - P_{damage}}{P_{norm}} \tag{10}$$

where V_p is the magnitude of performance vulnerability (a decrease in this value indicates a lack of robustness); P_{norm} is the performance parameter evaluated prior to disruption; and P_{damage} is the performance parameter evaluated after the disruption. Again, these parameters are typically measures of network connectivity pre-and post-disruption. Network analysis can be used to conduct robustness analyses at the campus and system levels.

Campus-Level Applications

Campus-level robustness evaluations are slightly more complicated than the general metrics mentioned under network analysis as they incorporate interdependencies between systems. Pinnaka et al. (2015) demonstrate this in a simplified example of the U.S. critical infrastructure network. Figure 9 shows the relationship of the 16 critical infrastructure systems (nodes) as a network and displays links as either unidirectional (black arrows) or bidirectional (red arrows). This method of network decomposition allows for an easy visualization of the complexity of a campus-level network evaluation.

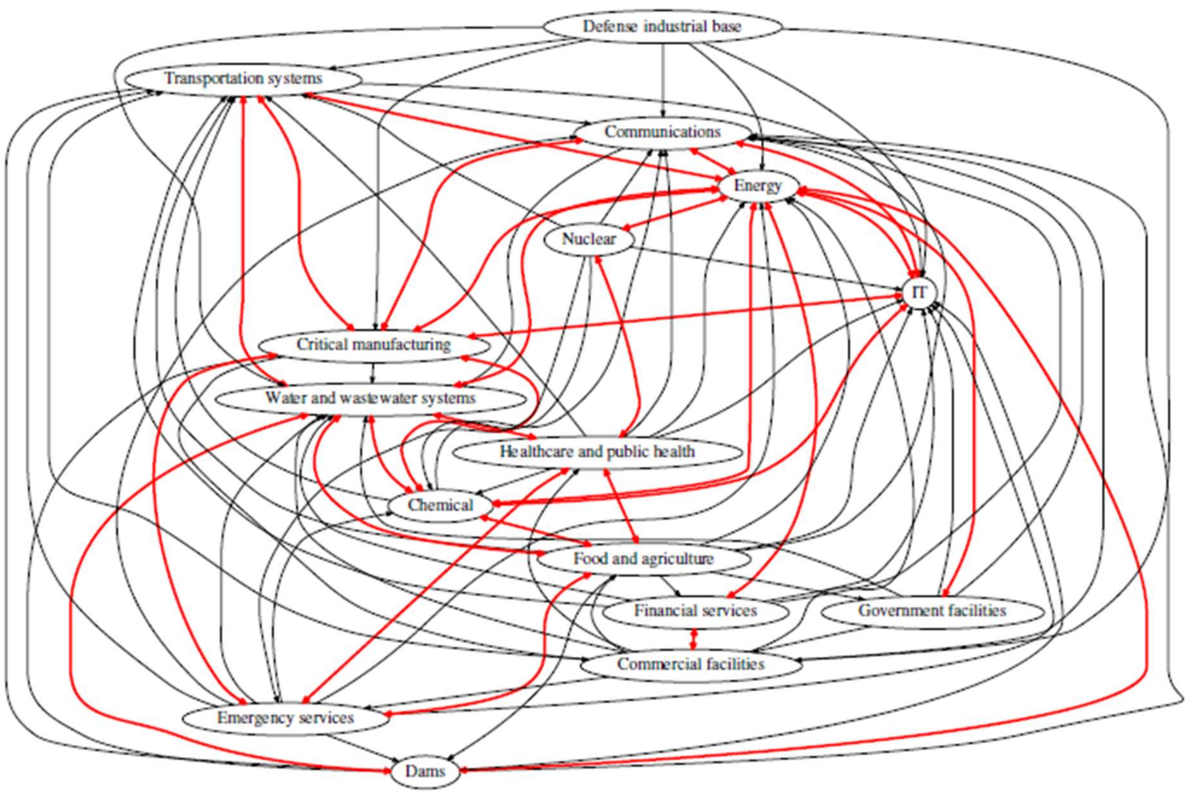

Figure 9: US Critical Infrastructure Network as modeled by Pinnaka et al (2015). Red arrows indicate bidirectional links. Black arrows indicate unidirectional links.

The authors then analyze the network to evaluate pre- and post-topological disruption metrics. Disruptions are modeled as targeted attacks to the highest-ranking centrality system, evaluated over degree centrality, closeness centrality, betweenness centrality, and eigenvector centrality. Eigenvector centrality is defined as the importance of individual infrastructure systems based on connections to high-degree nodes in the network (Pinnaka et al. 2015), then rank the 16 infrastructure systems based on post-disruption centrality outputs. This analysis method requires knowing the number of nodes, the directionality, and path length between nodes. It evaluates the robustness of the nodes in the network, as they are targeted and removed from the system. The output is a ranked list of the 16 infrastructure systems based on node robustness, evaluated over the four centrality metrics.

Additional methods of calculating network robustness include evaluating interdependent systems based on structural (topological) and functional performance (Wang et al. 2019a). Structural assessment of a network involves evaluating connectivity measures, including node degree, path length, clustering coefficient, betweenness, and giant component, both pre-and post-disruption. The clustering coefficient and giant component have not been previously defined. The clustering coefficient of a network measures the degree to which nodes tend to cluster together (Yassien et al. 2020). The giant component of the network is the largest connected series of nodes or links in a network, depending on whether nodes or links are to be added/removed to represent a disruption to the network (Duan et al. 2016). Yassien et al. (2020) described the giant component of the Canadian airport network as the largest connected group of airports after a disruption. The network robustness is then evaluated as a ratio of the giant component size post-disruption to the total number of connected airports in the network (Yassien et al. 2020).

System-Level Applications

System-level network robustness evaluations focus on the performance of the network post-disruption, typically measuring the capacity of the network to deliver to end-users post-disruption (Starita et al. 2018a). The focus shifts from analyzing failure modes, to what the system's functionality is in a degraded state, and broadly evaluates the robustness of the entire network by evaluating the robustness of both links and nodes (Yazdani and Jeffrey 2012). Network topology is still unique to the system being evaluated, but the failure mode is often a systematic removal of nodes and links to evaluate the resultant robustness.

Network performance evaluation is typically accomplished using flow-based metrics and comparing pre-and post-disruption values (Yassien et al. 2020, Yazdani and Jeffrey 2012). Examples of flow-based metrics include a passenger flow index evaluated across all nodes in a rail transit system (Starita et al. 2018a) and a ratio of the number and capacity of operational flights to and from an airport subject to a targeted attack (Yassien et al. 2020)

4.2.2 Robustness Index

A robustness index is used to provide a single value for a chosen level of robustness analysis, meaning the index is predominately evaluated over physical, often structural, characteristics of the component or system of interest. Similar to the vulnerability index, it consists of a weighted summation of robustness aspects, typically normalized across the summation of the weight criteria (Jelle et al. 2014). Equation 11 is a simplified representation of this notion, adapted from Jelle et al. (2014):

$$RI = \frac{\sum_{\mathrm{i}} w_i R_{\mathrm{i}}}{\sum_{\mathrm{i}} w_i} \tag{11}$$

where w_i is the weight or importance value; and R_i is the robustness aspect.

The inputs required to generate a robustness index focus are physical characteristics, such as construction materials and the hazards to which they are exposed, typically represented as some form of load (Jelle et al. 2014). These inputs are integrated using the robustness aspect portion of Equation 11. Robustness aspects include load factors, such as the type of load applied (live /dead loads, wind loads, hydrostatic loads) (Maes et al. 2006), and operational factors, such as ease of replaceability if damage occurs or occupancy change (Jelle et al. 2014). Robustness indices can be used to conduct robustness analyses at the system and component levels.

System-Level Applications

In the context of robustness indices, system-level can mean assemblies (smaller sub-sections of the larger system) or the entire system itself. An example of this is a modular building method, where smaller pre-built assemblies are combined to create the overall building (system) (Jelle et al. 2014). The robustness aspects (inputs) described above would be weighted and summed for the specific assembly features that also translate to the overall building. Jelle et al. (2014) displays this concept in a series of tables, laying out evaluation criteria unique to either the assembly or entire building and those that pertain to both. Table 4 below shows a truncated example of Jelle et al. (2014) results:

Table 4: Example Robustness Index Inputs adapted from Jelle et al. (2014)

System Category	Robustness Evaluation Aspects (Inputs)
Whole Building	RB1 = Climate Loads RB2 = Change in occupancy RB3 = Catastrophic Loads RB4 = Building Physical aspects

For example, RB4: Building Physical Aspects can be evaluated by breaking down the building into its material components, and evaluating the performance rating of the materials against the local building code and anticipated hazards. Jelle et al. (2014) assigned robustness aspect values between 0 and 100 based on this technique, then created six classes of robustness based on ranges of aspect values. After assigning weights (measures of importance) to each robustness evaluation input, a normalized robustness value can be generated for the entire building using equation 11.

Additional examples of this robustness index evaluation technique include bridges subject to earthquakes with displacement parameters as robustness aspect inputs (Domaneschi and Martinelli 2016), and a simplified building structure subject to a significant internal point load using loads and occupancy type as robustness aspect inputs (Maes et al. 2006).

Component-Level Applications

At the component level, robustness indices are evaluated over the construction materials themselves (Jelle et al. 2014). The generalized robustness equation described by Equation 11 still holds for use at the component level. The inputs for R_i are based on the performance of the materials subject to mechanical, climate, and catastrophic loads compared with localized requirements, ease of installation, range of use, and durability over the expected material lifetime

(Jelle et al. 2014). The robustness values can be assigned over a scale (0 to 100) (Jelle et al. 2014) or binary, if associated with a probability of failure (Maes et al. 2006).

4.3 Resilience Metrics

. In general, the goal of calculating a resilience metric is to quantify the response of a component, system, or campus subject to disruption and how well or fast it returns to equilibrium (Yodo and Wang 2016). Yodo and Wang (2016) suggest that there is no standardized method for assessing infrastructure resilience, since the definition of resilience varies based on the type of system, operating conditions, and magnitude of damage resulting from a disruption. This claim holds true in this thesis, as the quantity and variety of resilience metrics vary significantly from other measures. However, the most common metrics identified through this systematic literature review are resilience curves, resilience indices, and the use of network analysis. Section 4.3.1 identifies and explains the use of resilience curves. Section 4.3.2 identifies and explains the use of resilience indices. Section 4.3.3 identifies and explains the use of network analysis. Each metric is presented with the inputs required to conduct the analysis, the expected outputs. A brief discussion of the metric's levels of analysis follows (campus, system, and component level).

4.3.1 Resilience Curve

The resilience curve uses an analysis of a chosen performance metric over time, comparing pre-disruption, post-disruption, and recovery responses (Yodo and Wang 2016). A minimum of four time-series inputs are required to build a resilience curve, with degraded steady-state performance as an optional fifth input: 1) steady-state performance before disruption, 2) the unreliability profile immediately after disruption, 3) the degraded but steady-state performance over time (if applicable), 4) the recovery profile showing the performance improving towards pre-

disruption levels, and 5) full steady-state recovery performance (Yodo and Wang 2016). Steady-state performance before disruption defines the baseline performance value and records it over time. This is known as the reliability phase of the resilience curve, as shown in Figure 10. The unreliability profile captures the impact of a disruption on performance. These profiles are unique to the application level of analysis (component, system, campus) and the nature of the disruptive event. Three basic categories of unreliability profiles are seen in the literature. The first is where performance loss is sudden, and the disruption is unavoidable and causes destruction at one moment (a tornado uprooting a structure, for example (Nevill and Lombardo 2021)). The second is a gradual loss in performance over time that eventually stabilizes to a baseline performance level (a power distribution system subject to steadily increasing wind speeds (Panteli et al. 2017a)). The third is a gradual decline in performance that immediately transitions to a recovery profile once the minimum performance is achieved (multi-story buildings subject to earthquakes that undergo immediate repairs (Bonstrom and Corotis 2016)). All of these apply to the unreliability phase of the resilience curve, as shown in Figure 10. The recovery profile depicts how performance is recovered with respect to time. These profiles are estimated by a variety of functions (for example, linear, step-wise, lognormal) in nature and drive the method of evaluating resilience (Yodo and Wang 2016). These functions vary based on the performance measure, hazard, and how recovery operations are conducted. Full steady-state recovery performance is achieved as soon as recovery is complete. The focus of the following sections will be identifying proper recovery profiles, as they are the most significant driver in estimating resilience.

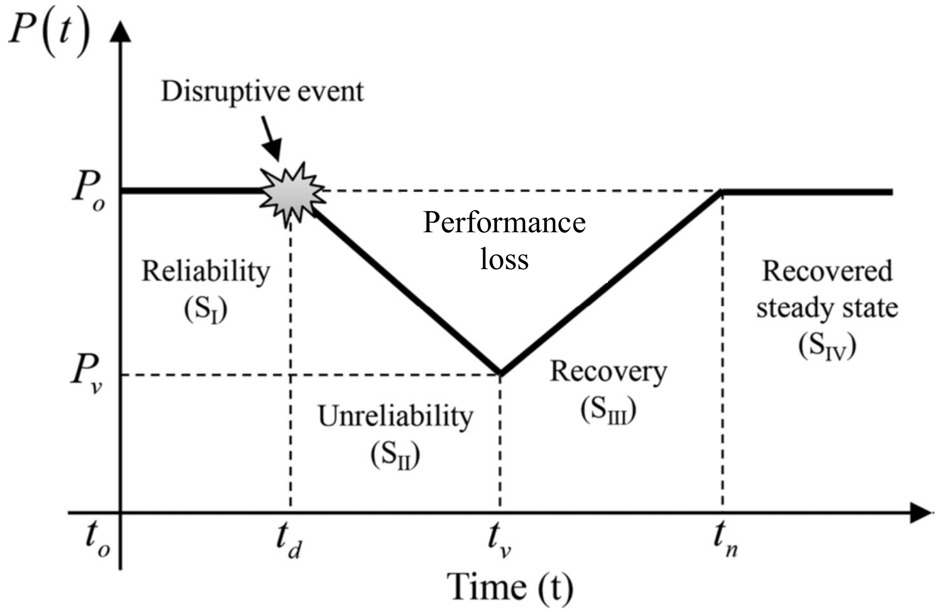

Figure 10: Generic Resilience Curve (Yodo and Wang 2016)

Ultimately, the output of a resilience curve is based on the calculation of the area containing the unreliability and recovery regions, defined as performance loss (Yodo and Wang 2016). Equation 12 shows the calculation of resilience using the resilience curve:

$$\psi_{loss} = \int_{t_o}^{t_n} (P_o(t_o)\text{-}P(t))dt \qquad (12)$$

where P_o is the performance metric evaluated at time 0 (t_o); and $P(t)$ is the baseline performance level over time interval t_o to t_n. t_n is the point in time at which full recovery has occurred, and where Ψ_{loss} represents resilience. The method in which Ψ_{loss} is calculated is primarily driven by the combination of unreliability and recovery profiles (Yodo and Wang 2016). Resilience curves conduct resilience analyses at the campus, system, and component levels over one performance measure at a time.

Campus-Level Applications

Campus level use of the resilience curve evaluates campus-level performance measures with respect to time. The unreliability profiles are represented as sudden performance loss at a moment in time, and various recovery profile functions are evaluated to estimate campus or community resilience (Abdelhady et al. 2020). Campus-level performance measures include the percent of the housed population over time (Abdelhady et al. 2020) and the percent of repairs left to complete over time (Sharma et al. 2020). An example of this application level is presented by Abdelhady et al. (2020). The authors define community or campus resilience as a function of the percent of the population housed before and after a hurricane. The performance measure of housed population is directly related to the ability of the community to recover residential buildings, making this an infrastructure resilience assessment. The unreliability profile of the housed population after a hurricane takes on a sudden form, where the ability to house people decreases to its minimum status immediately. The recovery profile is estimated as a step-wise function to account for three distinct stages of occupancy status over time: unsafe therefore unoccupied, partially safe therefore partially occupied, and safe therefore fully occupied. Resilience (percent of housed population over time) was compared for category 0 to category 5 hurricanes by overlaying the resilience curves associated with each hurricane category.

An additional example of the use of resilience curve include the degree of connectivity of residents to the larger infrastructure network, primarily focused on road access to critical facilities, after landslides, where historical residential access data was plotted over time, covering pre-and post-disruption through recovery, and resilience calculated as the ratio of pre and post disturbance

access (Bozza et al. 2017). The unreliability and recovery profiles were deterministic in nature based on historical road access data.

System-Level Applications

Based on this systematic review, the system level is the most common application of the resilience curve. At this level, the unreliability and recovery functions are unique to the system they are used to describe in addition to their response to the hazard, and performance measures are driven solely by the system itself (Panteli et al. 2017a, Yodo and Wang 2016). Examples of recovery functions include linear (Liu et al. 2018); concave and convex (Yodo and Wang 2016); and other non-linear forms (Panteli et al. 2017a). Examples of performance measures include the number of lines restored over time for a power distribution system (Panteli et al. 2017a), percent of structural functionality of bridges subject to earthquakes (Argyroudis et al. 2020b), and percent of standard output of a water distribution system subject to earthquakes (Petersen et al. 2018.

Examples of system-level resilience curve evaluation include a multi-story administrative building subject to explosions (Salem et al. 2017), and a power distribution system subject to various high-wind events (Mukherjee et al. 2020a).

Component-Level Applications

When using the resilience curve, the definition of component level is confined to connected assemblies that form the complete system (Mukherjee et al. 2020a). An example of this are bridges, which are considered part of the larger road transportation system (Argyroudis et al. 2020b). An example of component level use of the resilience curve is a bridge subject to seismic activity, represented by a sudden loss in functionality and approximating the recovery profile as linear (Argyroudis et al. 2020b). In this instance, resilience was evaluated as the ratio of percent

functionality of the bridge before disruption to after. Another example is the ground floor column structure of a multi-story office building subject to an earthquake, modeled as a sudden loss in performance and recovery approximated as linear immediately after reaching the degraded operational state (Hashemi et al. 2019). Resilience was evaluated as the percent of total functional columns after the disruption.

4.3.2 Resilience Index

Resilience indices provide application-specific temporal and spatial evaluations of resilience based on a wide range of performance and hazard inputs (Yodo and Wang 2016). This section does not include every index developed by researchers, as numerous depend on hazard, application, location, and time. However, major re-occurring indices are identified and discussed in further detail. The most significant benefit of resilience indices is the ability to compound the analysis of multiple performance measures over time. These indices are applicable at the campus, system, and component levels.

Campus-Level Applications

A typical implementation leverages all or part of the PEOPLES framework (outlined below) established by Renschler et al. (2010). This framework incorporates population and demographics (P), environmental considerations (E), organized governmental services (O), physical infrastructure (P), lifestyle and community competence (L), economic development (E), and social-cultural capital (S) considerations into one wholistic metric, PEOPLES (Renschler et al. 2010). This framework does not define specific performance measures or methods of evaluation for every dimension but instead widens the aperture from a strictly technological community resilience assessment and is applicable across any location and for any hazard. In

general terms, the PEOPLES framework is mathematically defined by equation 13 (Reinhorn and Cimellaro 2014):

$$Q_{TOT}(t) = Q_{TOT}(Q_{POP}, Q_{ENV}, Q_{ORG}, Q_{PHY}, Q_{LIF}, Q_{ECO}, Q_{SOC}) \tag{13}$$

where Q_{TOT} is the community functionality; Q_{POP} is the population and demographics functionality; Q_{ENV} is the environmental and ecosystem functionality; Q_{ORG} is the organized government services functionality; Q_{PHY} is the physical infrastructure functionality; Q_{LIF} is the lifestyle and community competence functionality; Q_{ECO} is the economic functionality; and Q_{SOC} is the social and cultural capital functionality. This framework is coupled with GIS software at the campus level to generate a spatial and temporal representation of resilience (Renschler et al. 2010). The calculation of the final resilience index is calculated as shown in Equation 14 over both space and time (Reinhorn and Cimellaro 2014):

$$R_{COM} = \int_{Ac} \frac{R(\vec{r})}{A_C} dr = \int_{Ac} \int_{t}^{t+T_{LC}} \frac{Q_{TOT}(t)}{A_C T_{LC}} dt\, dr \tag{14}$$

where $\vec{r}$ is a directional vector identifying the spatial location of the assessment; A_C is the total area of the selected evaluation region; T_{LC} is the desired time of analysis; and Q_{TOT} is the selection of all or some of the dimensions from Equation 13.

The inputs required to use this framework entirely depend on the location and hazard. However, a straightforward example is presented by Leandro et al. (2020), where a campus level resilience index was quantified for Munich City subject to extreme flooding. The authors selected the physical infrastructure, social, and economic dimensions of the PEOPLES framework and generated functionality measures for each. For the physical infrastructure dimension, the authors modeled the functionality of residential buildings subject to flood damage based on total flood

depth, flood duration, and rate of water accumulation compared to the volume of water each residential structure could handle before failure. The authors quantified functionality as a percentage of a residential structure occupied by the elderly and children compared to baseline parameters for the social dimension. Finally, the authors quantified functionality as the annual household income compared to a reference parameter for the economic dimension. These dimensions were assigned weights according to perceived importance and evaluated spatially and temporally using GIS software.

Additional examples of the use of the PEOPLES framework include a community resilience evaluation of Tohoku, Japan, after the 2011 earthquake, incorporating multiple physical infrastructure failures in the power, water, and gas systems (Cimellaro et al. 2014a), the evaluation of San Francisco after the 1989 Loma Prieta Earthquake (Kammouh et al. 2019).

System-Level Applications

At the system level, resilience indices can be developed by direct integration of the performance loss portion of the resilience curve (Yodo and Wang 2016) or generated as a weighted sum of factors, such as the PEOPLES framework (Renschler et al. 2010).

Direct integration of the resilience curve over the time interval of performance loss is accomplished using Equation 15 (Yodo and Wang 2016):

$$\psi_{loss} = \frac{\int_{t_o}^{T^*} AP(t)\, dt}{\int_{t_o}^{T^*} BP(t)\, dt} \tag{15}$$

where *AP(t)* is the performance area under the resilience curve after disruption; *BP(t)* is the baseline performance area prior to disruption; T^* is a future point in time after recovery is complete; and t_o is the initial time pre-disruption. Inputs required to utilize this index are a

performance measure specific to the system, such as electrical output (capacity) for an electrical distribution system subject to a hurricane (Ouyang et al. 2012).

Generation of indices as a weighted sum of factors considers more than just the system's structural (functional) failure (Argyroudis et al. 2020b). Additional considerations include socio-economic impacts due to performance degradation. In these instances, the inputs required to evaluate a resilience index expand to include knowledge of the local impacted area from a social and economic standpoint (Argyroudis et al. 2020b). An example includes a closed bridge due to degraded performance, thus rerouting traffic around potential businesses (Argyroudis et al. 2020b). These additional inputs are weighted in conjunction with the performance evaluation of the physical infrastructure based on perceived importance. An example is the resilience index generated for a water distribution network subject to an earthquake, encompassing local water demand, actual water levels, and water quality (Cimellaro et al. 2016b).

Additional examples include drainage systems (Mugume et al. 2015), transportation networks (Kilanitis and Sextos 2019), water distribution systems (Cimellaro et al. 2016b), and power transmission systems (Yang et al. 2018).

Component-Level Applications

The resilience index is defined in terms of performance measures and recovery models and restoration functions that are unique to the components themselves at the component level. Like system-level resilience analyses, these indices can be derived from a resilience curve generated for a given component (Argyroudis et al. 2020b). Examples include fluid distribution components subject to an earthquake, where performance was evaluated as repair time and repair cost over time and resilience defined in terms of both of these measures (Singhal et al. 2019), and structural

members of a multi-story building subject to blast damage where resilience was evaluated as a function of individual member repair time and cost (Salem et al. 2017).

4.3.3 Network Analysis

In the context of resilience, network analysis metrics predominately evaluate either node or link resilience subject to different failure modes (Wang et al. 2019a). The network topography is driven by the characteristics of the network involved, while the failure mode (previously described in section 4.2.2) is driven by the hazard the network is exposed to (Wang et al. 2019a). The inputs required to use these network analysis metrics require proper topological representation of the network (correct placement of nodes, directionality considerations to travel through the network, and length of paths through the network) and an accurate failure mode to represent the hazard the network is exposed to. Measures of connectivity, including node degree, path length, and betweenness, are evaluated across nodes and links in the network prior to a disruptive event and are directly compared to the same calculations conducted post-disruption (Yazdani and Jeffrey 2012, Dong et al. 2019, Yodo and Wang 2016).

The expected output using this method evaluates network performance loss due to a specific type of failure. Equation 16, adopted from (Yodo and Wang 2016), demonstrates this as a ratio of pre-and post-disruption performance:

$$\Psi = \frac{V_{initial} - V_{loss}}{V_{initial}} \quad (16)$$

where Ψ is the magnitude of performance loss; $V_{initial}$ is the flow performance parameter evaluated prior to disruption; and V_{loss} is the flow performance parameter evaluated after the disruption. Again, these parameters are typically measures of network connectivity pre-and post-

disruption. Network analysis can be used to conduct resilience analyses at the campus and system levels.

Campus-Level Applications

At the campus level, network analysis is used to map the interconnections between and within systems that a community relies on, such as power systems, gas systems, water systems, communication systems, and road and transportation systems (Mao and Li 2018). These systems are often analyzed independently, using key network indicators, such as measures of centrality, the number of shortest paths through the network, the number of disrupted nodes, and clustering, then are scaled up to generate a campus-level resilience indicator (Cimellaro et al. 2011a). The resilience output is defined as the performance loss of the network, evaluated using equation 16 over all nodes and links in the network. This method has been used to assess the resilience of transportation networks ((Cimellaro et al. 2011a), (Cavallaro et al. 2014)), and the interconnectedness of communication networks with electric and water systems (Mao and Li 2018).

System-Level Applications

Resilience network analysis seeks to break a system into a series of nodes (built infrastructure) and links (existing connections between nodes), then, through a perturbance method, disrupts the network and measures the resilience of the system by comparing pre-and post-disruption measures, such as various measures of centrality (Mao and Li 2018). This method has been used to analyze roadway systems ((Xu et al. 2020), (Aydin et al. 2018)), and water supply and distribution networks ((Farahmandfar et al. 2017), (Pagano et al. 2019)).

5.0 Analysis & Discussion

The novelty of this research lies in the systematic identification of resilience, robustness, and vulnerability metrics and the proposed taxonomy. This section synthesizes major connections between the metrics discussed above, identifies any potential gaps existing in literature, and discusses any challenges encountered within the metric taxonomy presented. Large-scale recommendations for Air Force applications and future focus areas are provided through a by-measure discussion of potential Air Force infrastructure applications. To reiterate terminology used throughout this research, a metric is defined as the specific quantifier used to calculate a numerical value for vulnerability, robustness, and resilience, independent of analysis level. A measure is defined as producing some quantitative assessment of resilience, robustness, or vulnerability. The analysis level is defined at the component, system, or campus levels.

5.1 Air Force Applications

As previously mentioned in the introduction, the Air Force infrastructure portfolio is costly and diverse, both spatially and in use. With Presidential Directive 21 mandating a shift to invest in resilient infrastructure, the Air Force is obliged to comply, but must do so within the congressional budgetary constraints unique to the DoD. It is therefore advantageous to define and quantify infrastructure resilience based on data and resources currently available, Air Force wide. The purpose of this research was to identify existing resilience, robustness, and vulnerability metrics in use in industry and provide high-level recommendations and insights for their adaptation to Air Force infrastructure. This section serves to link the general results presented in the previous section to the Air Force, its infrastructure, and identify potential inputs and outputs from each metric.

Vulnerability

Vulnerability assessments are one of the few assessments the Air Force has already implemented, at least from a security standpoint. For example, Force Protection Conditions (FPCON) are enforced based on a degree of vulnerability and suspected targeted attack. The Air Force stands to benefit the most from investing in vulnerability indices and fragility curves. Topographic network analysis can be useful at the system level across an installation because path length, nodes, and directionality are readily available. For example, length of horizontal networks (water distribution, electrical transmission lines, roads), identification of major intersections, and knowledge of the directional nature of these systems is information stored in real property records. The challenge would be modeling the network and fully modeling the effects of node and link removal on the rest of the system. Section 4.1.3 shows that this is more complicated to achieve and requires extensive mathematical approximations and modeling. For this reason, the rest of this section will focus on fragility curves and vulnerability indices.

Vulnerability indices have the potential to provide the most useful evaluation of vulnerability at the component and system levels, then easily combined to a campus level assessment. Inputs such as component or system age, condition (based on the facility condition index), number of repairs, mission importance (based on the tactical mission dependency index) can all be included in a vulnerability index. These inputs can then be weighted based on the perceived importance of each one. This evaluation might be more beneficial for base civil engineers to communicate specific system vulnerabilities to leadership. The weighting of each input can be adjusted according to the system, specific past and future investments (repair or

restoration projects), and the amount of risk leadership is willing to invest. Vulnerability indices in particular is the most versatile, from an input standpoint.

Fragility curves are an excellent way to present a simple, two-dimensional mechanism for communicating probability of failure of a system or component subject to hazard intensities. The manipulation of the inputs required to generate these curves is more complicated. However, communication of probability of failure to leadership is one of the most valuable outputs from this metric. This is the main benefit of this metric.

Robustness

The utility of robustness metrics is like that of vulnerability metrics. Network analysis was the most common metric found through this systematic literature review but would be the most complicated to implement. Again, the topological information required to generate a system-level network is readily available in the Air Force Sustainment Management Systems (SMS) systems. The complexity lies in understanding how failure modes impact the rest of the system. At the campus level, modeling the interconnections of the major infrastructure sectors on an installation would be highly beneficial, but determining the path lengths would be complicated. Robustness indices can be used to evaluate systems and their subsequent components but does not translate well to a campus-level assessment that incorporates other non-infrastructure impacts. Air Force inputs could include specific materials and their condition, identified through the work breakdown structure used by BUILDER, age and climate factors specific to the installation location.

Resilience

The resilience metrics that could be implemented across the Air Force are the resilience curve and the resilience index. Network analysis could be useful to display the interconnections

between systems across the installation but determining directionality and path-lengths would require consensus across all base entities. The primary focus of discussion here is the resilience curve and index.

The utility of the resilience curve is that it is a simple display of performance over time. It can be used to communicate operational resilience, which is the ability to meet some end user demand, or physical infrastructure resilience, particularly at the system level. The curve integrates easily with deterministic data but can also be adapted to include uncertainty using confidence intervals to communicate risk and can also be translated to a more future-focused evaluation through probabilistic representations of unreliability and recovery profiles. The required inputs of performance measures, unreliability profiles, and recovery profiles may seem complicated, but the Air Force already possesses the data required to generate these inputs. Component and system-level derivations of the resilience curve are possible with the data provided by SMS's such as BUILDER and NexGen IT. A performance measure, such as the percent of functional power lines after a windstorm can be generated from existing work-order data from NexGen IT and plotted over time. This could be accomplished in any worksheet software; that is, no advanced modeling software is required. Once the data is plotted, the unreliability and recovery profiles can be approximated using the estimation techniques presented in section 4.3.1 based on their shape and a deterministic resilience measure can be calculated using simple geometric shapes. While this information quantifies resilience for a single performance measure after a disaster, the implementation of confidence intervals can be applied to recovery profiles to communicate uncertainty and ultimately assist portfolio managers and base civil engineers in communicating risk to leadership. Another benefit to using resilience curves is the ability to plot multiple recovery

profiles based on different adaptation or repair strategies. This rate-of-recovery is driven by adaptation measures implemented prior to or repair efforts immediately following a disruption. For example, a resilience curve could be generated for the percent of functional space of a building after flood inundation. If no adaptation measures were taken, the rate of recovery would be expected to be slower than if sandbags were placed at all doors and openings. These two scenarios could be plotted on the same curve, showing that it would be advantageous to place sandbags before the flood occurs.

Resilience indices can quantify and capture the effects of multiple functionality performance measures over time. Multiple resilience curves estimating performance loss can be combined using a single weighted index. These weights can reflect the level of risk base civil engineers or even wing commanders are willing to accept after a disaster. They can also assess and incorporate other aspects of community resilience before and after disruption, making them ideal for an installation-level analysis. Air Force specific inputs could be the ratio of the number of junior enlisted members living in dorms versus the rest of the force living off base or the number of memorandums of agreement with the local community. The Air Force could quantify the impacts of these inputs from a resilience standpoint and determine minimum benchmarks during each phase of resilience.

General Example

As a general example, a Base Civil Engineer (BCE) may decide to conduct a resilience, robustness, and vulnerability assessment of the entire road network across their installation. At this decision level, analysis could follow the work breakdown structure found in BUILDER, such that a component-level analysis could include curbs, gutters, traffic lights, manhole covers, and

road markings, which would be of interest to BCEs and specific shops in the operations flight. A system-level analysis could include intersections, entry and exit gates and specific segments of road and would primarily be of interest to BCEs and in-part to higher leadership (for example. entry and exit gates would be of greater concern to higher leadership than a specific intersection). A campus-level analysis would include the entire road network and its integration with base entities, which would be of interest to the highest base level leadership.

At the component level, resilience would be best evaluated using resilience curves for each component. Performance metrics at this level of analysis could include percent functionality (potentially represented using a sudden decline in performance for the unreliability profile and a step-wise recovery function), condition index over time (potentially represented using a gradually declining unreliability profile followed by degraded steady-state performance and a linear or step-wise recovery profile). Robustness would be best evaluated using the robustness index with weights determined using multiple criteria decision making over inputs such as age and material composition. Vulnerability would be best evaluated using a vulnerability index with weights determined using multiple criteria decision making over inputs such as date of last repair, number of repairs (or workorders), and condition index.

At the system level, resilience would be best evaluated using a resilience curve over performance metrics such as length of usable road or number of vehicle passes over time. The unreliability profile could potentially be represented as a sudden drop unreliability profile with an immediate linear recovery profile. Robustness could be evaluated using a robustness index over the system materials, age, and condition, with weights determined by multiple criteria decision making. Vulnerability should be evaluated using the fragility curve, as it is best suited for system

level analysis. The intensity measures would be drive by the potential hazard (flooding, for example) and damage states could be identified using the HAZUS technical manual or derived from condition indices. The curves themselves could be evaluated over the road type (asphalt or concrete).

At the campus level, resilience would be best evaluated using the resilience index and following the PEOPLEs framework. Population inputs could include percent of the base population broken out by rank. Environmental inputs could include a ratio of impacted wetland areas pre-and post-disruption. Organized government service inputs could include a ratio of on-base (or off-base) hospital wait times pre-and post-disruption. Physical infrastructure inputs would be specific to the road network and could be a weighted and normalized combination of system-level percent functionality outputs using the resilience curve. Lifestyle inputs could include the percent obligation of base-services (first responders) to off-base events as defined by MOAs with the community. Economic considerations could include impacts to non-appropriated funds (NAF) facilities as they don't receive appropriated funds. Robustness would be best evaluated using network analysis, despite its complexity. Each of the systems identified above (intersections, entry and exit gates) would be nodal inputs, along with important base resources (such as the airfield and base hospital), while road segments between the systems would be considered links. Measures of connectivity such as node degree, betweenness centrality, accessibility and efficiency could be evaluated pre- and post-disruption. Connections between specific nodes and important base resources should be the primary concern when conducting mode and link removal to evaluate robustness. Vulnerability should be evaluated using the vulnerability

index, with the inputs generated from system-level use of fragility curves and the tactical mission dependency indices (TMDI) of important base resources (such as the airfield or base hospital).

5.2 Connections

Metric connections exist in two forms: 1) those that cross levels of analysis within a measure, such as the resilience index, and 2) those that cross measures within a level of analysis (for example, a metric that translates from vulnerability to robustness to resilience within the system level). The discussion provided below is organized by measure from resilience to vulnerability, then by level of analysis from component to campus levels.

Resilience

Starting at the component level, and progressing to the system to the campus level of analysis, the resilience index and resilience curve were the most frequently proposed metrics found in the literature. It is important to understand that the curve and indices were not always calculated independently. Often, indices are calculated from a resilience curve as an integration of the area of performance loss (Yodo and Wang 2016). However, they could be calculated independently based on pre-and post-disruption performance based on time-series flow data. That both the index and curve can be used at, or between, any level of analysis shows the versatility these metrics.

Robustness

The robustness index can be used to calculate strength at component and system levels but was not found to be applicable at the campus level. The inability for the metric to be used across all levels of analysis suggests that campus level robustness assessments consider too many

interdependent components and systems to calculate a useful value. Robustness is also focused on the innate structural ability to withstand damage, making it difficult to incorporate other factors needed to produce a campus level assessment.

Vulnerability

Fragility curves and vulnerability indices translated across all levels of analysis. Like the resilience curve and index, vulnerability indices can be calculated from fragility curves, but also independently. The calculation of each requires a known data type of hazard and nature of exposure.

Level of Analysis

In terms of crossing between measures, no single metric provides that range. The possibility of crossover between measures would suggest that measures are interrelated to one another. While it is true that robustness and vulnerability values can be used to generate resilience data, the modifications required to make this transition fundamentally change the metric and require different inputs. As an example, at the component level, robustness is typically a combination of material characteristics, typically displayed in the form of a robustness index. A vulnerability index requires the identification of a hazard, a degree of exposure, and some knowledge of potential failure/damage states at various intensities of the hazard. The resilience index requires knowledge of the performance of the component over time pre-and post-disruption. Robustness and vulnerability indices appear to be calculable independently from each other but are commonly used as steppingstones to calculate a resilience value for a given component.

5.2 Gaps

Within the field of existing resilience, robustness, and vulnerability metrics, several areas are better defined than others. It is important to note that "well-defined" does not necessarily refer to the number of relevant articles or indexes found, but rather their quality, cohesion, and range of use. To illustrate this, at the system level, vulnerability indices were utilized in 30% of the articles analyzed, hazard-dependent versus system-dependent, and were scalable from the component to campus levels. As a comparison, resilience indices were utilized in 51% of the articles analyzed, system-dependent, and were translatable from the component to system level, as long as the parameters used to generate the index did not vary. The system-dependency of resilience indices makes it difficult for researchers to agree upon the implementation of this metric to create a standardized, and easily accessible, metric due to the potentially infinite system configurations. Vulnerability indices being hazard-dependent creates a finite number of applications that then are modified to fit the system being analyzed, making vulnerability indices more cohesive, easier to access, and improve their quality.

5.3 Challenges & Recommendations

Several challenges are presented in the aggregation of select metrics. First, the level-of-analysis proved especially difficult, as not all literature defined the analytical boundaries in the same way. This was most pronounced at the component level. To illustrate this, some literature classified a bridge as a component of a larger transportation system (Argyroudis et al. 2020b)), while others classified the structural members of the bridge as components with the bridge as the system (Jelle et al. 2014). This discrepancy in the boundaries of each of the levels-of-analysis makes fitting metrics into crisp levels of analysis complicated. To simplify this issue, this research

focused on the use of the term component and other synonyms versus defining an arbitrary boundary for each level of analysis, to ensure a wholistic analysis of existing literature on resilience, robustness, and vulnerability metrics.

Second, individual measures were not calculated uniquely from other measures. This lack of independence made selecting the attributes unique to a metric difficult without crossing into defining another measure. As an example, resilience was often quantified in terms of some level of vulnerability (Argyroudis et al. 2020b) and/or robustness (Woods 2015). This was overcome by recognizing that an article that defined a measure in terms of other measures was used to define all the measures it presented, not merely the predominate one listed as the goal of the article.

Third, some measures were more rigidly defined compared to others. This was made evident by a combination of the number of articles applicable to a measure and the number of metrics identified within a measure at a specific level of analysis. Robustness is well defined in literature, and as a result, the number of metrics found to quantify robustness were fewer and more cohesive than resilience. The solution to this problem lies in future research dedicated to the less cohesive measures, such as resilience.

6.0 Conclusion

The cumulative review of literature collected here suggests that the implementation of resilience, robustness, and vulnerability metrics can be dictated by the intended level of application. Based on this, a simple by-level taxonomy is proposed for these metrics. The outcome of this review quantified resilience, robustness, and vulnerability at the component level, then combined these metrics in a meaningful way at the facility or system level, and finally at the campus level and provided large-scale recommendations for Air Force implementation. Providing a quantitative summary of resilience, robustness, and vulnerability at each of these levels would equip leaders at all levels with a holistic picture of their portfolio's potential performance in adverse conditions. General recommendations for moving this field of research forward include a potential shift from system-dependent to hazard-dependent metrics, especially for compounding metrics such as resilience indices. To make this research more accessible to the Air Force, the current availability of sustainment data should be analyzed and compared with the data required to use all metrics found in this literature review. From there, down selecting the most applicable metrics based on available data and identifying what additional data will be required is the next logical step. The major value this research provides is a consolidated and organized presentation of available resilience, robustness, and vulnerability metrics along with their required inputs and expected outputs. In the context of the Air Force, many of these metrics can be implemented with data already available at installations. It provides the first step in defining and quantifying resilience, robustness, and vulnerability in the context of infrastructure decision making.

Appendix

Supplemental Articles

Vulnerability Articles - CAMPUS

(Abdelhady et al. 2020)

(Abebe et al. 2018)

(Aguilar-Meléndez et al. 2019a)

(Amin et al. 2020)

(Anelli et al. 2019)

(Arun Kumar and Kunte 2012)

(Bagdanavičiute et al. 2015a)

(Dall'Osso et al. 2010)

(Espada et al. 2015)

(Feng et al. 2017)

(Hereher et al. 2020)

(Honesti et al. 2015a)

(Ismail et al. 2012)

(Jevrejeva et al. 2020)

(Kantamaneni 2016a)

(Kantamaneni et al. 2019)

(Kaynia et al. 2008)

(Kermanshah et al. 2017a)

(Lam et al. 2014a)

(Li et al. 2020)

(Liu et al. 2017)

(Malgwi et al. 2020)

(Mitoulis et al. 2019a)

(Mohd et al. 2018)

(Nazemi and Dehghanian 2020a)

(Nazemi et al. 2020a)

(Ogie et al. 2016)

(Papathoma-Köhle 2016)

(Papathoma-Köhle et al. 2019)

(Pitilakis et al. 2019)

(Rahmadi 2020)

(Rajasree and Deo 2020)

(Sheik Mujabar and Chandrasekar 2013)

(Starita et al. 2018a)

(Tonmoy et al. 2015)

(Vera San Martín et al. 2018a)

(Wang et al. 2014)

(Yu et al. 2018)

(Zhang et al. 2018a)

(Zio et al. 2008a)

<u>Vulnerability Articles – SYSTEM</u>

(Ismail et al. 2012)

(Tsinidis et al. 2019b)

(Mukherjee et al. 2020a)

(Malgwi et al. 2020)

(Morán-Rodríguez and Novelo-Casanova 2018)

(Cavaleri et al. 2017)

(Aguilar-Meléndez et al. 2019b)

(Mishra et al. 2021b)

(Oboudi et al. 2020)

(Beyza et al. 2019b)

(Kemp 2007)

(Starita et al. 2018b)

(Lam et al. 2014b)

(Delorto 2017)

(Alipour et al. 2014)

(Argyroudis et al. 2020c)

(Kantamaneni 2016b)

(Hughes et al. 2021)

(Hines et al. 2010)

(Nazemi et al. 2020b)

(Zheng et al. 2020)

(Cogswell et al. 2018)

(Kilanitis and Sextos 2019b)

(Azarm et al. 2018b)

(Hashemi et al. 2019)

(Maltinti et al. 2012)

(Honesti et al. 2015b)

(Achillopoulou et al. 2020)

(Dey et al. 2018)

(Abedijaberi and Leopold 2019)

(Bagdanavičiute et al. 2015b)

(Zhang et al. 2018b)

(Vera San Martín et al. 2018b)

(Panteli et al. 2017c)

(Zhou et al. 2020)

(Mitoulis et al. 2019b)

(Athmani et al. 2015)

(Ferreira et al. 2013)

(Nazemi and Dehghanian 2020b)

(Wang et al. 2019a)

(Panteli and Mancarella 2015b)

(Atef and Moselhi 2013)

(Kermanshah et al. 2017b)

(Van De Lindt et al. 2019)

(Wang et al. 2017c)

(Zio et al. 2008b)

(Pitilakis et al. 2019)

(Li et al. 2020)

(Mhatre et al. 2018)

Vulnerability Articles – COMPONENT

(Mukherjee et al. 2020a)

(Malgwi et al. 2020)

(Morán-Rodríguez and Novelo-Casanova 2018)

(Benavent-Climent 2011)

(Argyroudis et al. 2020c)

(Nazemi et al. 2020b)

(Azarm et al. 2018b)

(Hashemi et al. 2019)

(Achillopoulou et al. 2020)

(Athmani et al. 2015)

(Ferreira et al. 2013)

Robustness Articles – CAMPUS

(Tonmoy et al. 2015)

(Duan et al. 2016)

(Faturechi and Miller-Hooks 2014)

(Dehghanian et al. 2018)

(Pinnaka et al. 2015)

(Dong et al. 2019)

(Yazdani and Jeffrey 2012)

Robustness Articles – SYSTEM

(Duan et al. 2016)

(Yassien et al. 2020)

(Alipour et al. 2014)

(Domaneschi and Martinelli 2016)

(Dehghanian et al. 2018)

(Das et al. 2020)

(Pinnaka et al. 2015)

(Ongkowijoyo and Doloi 2018)

(Ribeiro et al. 2013)

(Dong et al. 2019)

(Yazdani and Jeffrey 2012)

(Wang et al. 2019a)

Robustness Articles – COMPONENT

(Biondini 2009)

(Yassien et al. 2020)

(Domaneschi and Martinelli 2016)

(Ribeiro et al. 2013)

(Dong et al. 2019)

(Jelle et al. 2014)

(Maes et al. 2006)

Resilience Articles – CAMPUS

(Shahraeini and Kotzanikolaou 2020)

(Abdelhady et al. 2020)

(Faturechi and Miller-Hooks 2014)

(Francis and Bekera 2014)

(Mahmoud and Chulahwat 2019)

(Xu et al. 2020)

(Bazargani and Bathaee 2018)

(Anelli et al. 2019)

(Dell'Isola et al. 2020)

(Liao et al. 2018)

(Leandro et al. 2020)

(Ouyang et al. 2012)

(Bozza et al. 2017)

(Jonkeren and Giannopoulos 2014)

(Vamvakeridou-Lyroudia et al. 2020)

(Schultz and Smith 2016)

(Mao and Li 2018)

(Cavallaro et al. 2014)

(Ladipo et al. 2019)

(Salem et al. 2017)

(Panteli et al. 2016)

(Nan et al. 2016)

(Cimellaro et al. 2014a)

(Cimellaro et al. 2011a)

(Cimellaro et al. 2013)

(Zobel 2010)

(Reinhorn and Cimellaro 2014)

(Cimellaro and Solari 2014)

(Kamissoko et al. 2019)

(Petersen et al. 2018)

(Gardner et al. 2016)

(Renschler et al. 2010)

(Cimellaro et al. 2018)

(Wang et al. 2017a)

(Yodo and Wang 2016)

(Xiong et al. 2020)

(Béné and Doyen 2018)

(Zhao et al. 2017)

(Angeles et al. 2019)

(Aydin et al. 2018)

(Cimellaro et al. 2015)

(Dehghanian et al. 2018)

(Feng et al. 2017)

(Chang and Shinozuka 2004)

(Baroud and Murlidar 2018)

(Miles 2014)

(Easton and Beruvides 2018)

(Bhatia et al. 2015)

(Cimellaro et al. 2016a)

(Khetwal et al. 2019)

(Cimellaro 2016)

(Cimellaro et al. 2014b)

(Merschman et al. 2020)

(Nasrazadani and Mahsuli 2020)

(Broccardo et al. 2015)

(Sharma et al. 2020)

(Romanazzi et al. 2018)

(Argyroudis et al. 2020a)

(Kammouh et al. 2019)

(Barker et al. 2013)

(Zhang and Wang 2016)

(Chmielewski et al. 2016)

(Liu and Song 2020)

(Mitoulis et al. 2019b)

(Poudel et al. 2020)

(Mukherjee et al. 2020b)

(Fischer et al. 2019)

(Kahnamouei et al. 2017)

(Zhu et al. 2020)

(Cimellaro et al. 2011b)

(Bertilsson et al. 2019)

(Abenayak et al. 2018)

(Ogie et al. 2016)

(Espada et al. 2015)

<u>Resilience Articles – SYSTEM</u>

(Lin et al. 2019)

(Shahraeini and Kotzanikolaou 2020)

(Mukherjee et al. 2020a)

(Mugume et al. 2015)

(Cetiner et al. 2019)

(Xu et al. 2020)

(Bazargani and Bathaee 2018)

(Liu et al. 2018)

(Nan and Sansavini 2017)

(Nan et al. 2014)

(Liao et al. 2018)

(Mishra et al. 2021b)

(Leandro et al. 2020)

(Hadachi and Albayrak 2019)

(Oboudi et al. 2020)

(Ouyang et al. 2012)
(Phillips et al. 2020)
(Jonkeren and Giannopoulos 2014)
(Albasrawi et al. 2014)
(Wang et al. 2019b)
(Mao and Li 2018)
(Ladipo et al. 2019)
(Salem et al. 2017)
(Panteli et al. 2016)
(Nan et al. 2016)
(Cimellaro et al. 2011a)
(Cimellaro et al. 2013)
(Farahmandfar and Piratla 2018)
(Zobel 2010)
(Kamissoko et al. 2019)
(Argyroudis et al. 2020c)
(Joyce et al. 2018)
(Petersen et al. 2018)
(Balakrishnan and Zhang 2020)

(Gardner et al. 2016)
(Singhal et al. 2020)
(Ji and Wei 2016)
(Domaneschi and Martinelli 2016)
(Krishnamurthy and Kwasinski 2016)
(Wang et al. 2017a)
(Yodo and Wang 2016)
(Bonstrom and Corotis 2016)
(Xiong et al. 2020)
(Béné and Doyen 2018)
(Zhao et al. 2017)
(Kilanitis and Sextos 2019b)
(Aydin et al. 2018)
(Cimellaro et al. 2015)
(Hashemi et al. 2019)
(Dehghanian et al. 2018)
(Das et al. 2020)
(Reed et al. 2009)

(Panteli et al. 2017a)
(He and Cha 2019)
(Easton and Beruvides 2018)
(Achillopoulou et al. 2020)
(Bhatia et al. 2015)
(Cimellaro et al. 2016b)
(Kwasinski 2016)
(Khetwal et al. 2019)
(Ganin et al. 2016)
(Najarian and Lim 2020)
(Cimellaro et al. 2016a)
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(Merschman et al. 2020)
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(Poudel et al. 2019)
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(Liu and Song 2020)

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(Ongkowijoyo and Doloi 2018)

(Mukherjee et al. 2020b)

(Samadian et al. 2019)

(Kahnamouei et al. 2017)

(Panteli and Mancarella 2015b)

(Zhu et al. 2020)

(Bertilsson et al. 2019)

(Pagano et al. 2019)

<u>Resilience Articles – COMPONENT</u>

(Shahraeini and Kotzanikolaou 2020)

(Mukherjee et al. 2020a)

(Liu et al. 2018)

(Ladipo et al. 2019)

(Salem et al. 2017)

(Zobel 2010)

(Kamissoko et al. 2019)

(Argyroudis et al. 2020c)

(Joyce et al. 2018)

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13. SUPPLEMENTARY NOTES

14. ABSTRACT
Tyndall AFB was nearly destroyed after a category five hurricane named Michael tore through the Florida panhandle in 2018. A Program Management Office was stood up to coordinate, plan, and carry out the rebuild efforts of Tyndall AFB. The office's primary responsibility is "building a base capable of supporting a 21st-century mission while also focusing on structural resiliency and efficiency" (Laidlaw 2019). Despite the requirement to build a resilient infrastructure portfolio, the United States Air Force has yet to fully quantify and qualify measures of resilience, including robustness and vulnerability, in the context of their current built infrastructure portfolio. This research defines resilience, robustness, and vulnerability in the context of built infrastructure and proposes an easily accessible taxonomy of metrics to quantify each of these terms. A systematic review of literature explored the public sector's use of resilience, robustness, and vulnerability metrics. Key takeaways include identifying required data inputs for executing the metrics, a generalization of the outputs of each metric, and potential ways for the USAF to leverage each metric with existing SMS data. The resultant metrics identified are then categorized based on the level of analysis used to execute them (campus level, system level, component level metrics). Future endeavors include down-selecting metrics to those most readily implementable by USAF engineers.

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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