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A value-focused thinking approach to measuring community resilience

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after a degree is conferred.

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DEDICATION

I would like to dedicate this thesis to my parents, Suresh and Sarita, and my brother, Raunaq, without whose support I would not have been able to complete this work.

I would also like to dedicate this thesis to Dr. Cameron MacKenzie, whose continued support made this thesis possible.

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ABSTRACT

Community resilience is an important component of long- term planning for a town or a city. Resilience generally refers to the ability of a system or a community to withstand a disruption and to recover from a disruption, but specific definitions and measures for resilience can vary widely from researcher to researcher or from discipline to discipline. Community resilience is often measured using a set of indicators based on census, socioeconomic, and community organizational data, but little research has attempted to assess how closely these measures correlate with a community's ability to withstand or recover from a disruption. Engineering resilience metrics often are based on the "resilience triangle" concept. The resilience triangle assesses the loss in performance for a system and the time until the system's performance returns to its pre-disruption (or a better) state. Although these concepts can be applied to community resilience, determining appropriate metrics for the performance of a community remains a difficult challenge. This research proposes to measure community resilience based on value-focused thinking. We propose an objectives hierarchy that begins with a community decision makers' fundamental values or objectives for community resilience. Each of these five objectives is further broken down into measurable attributes that focus on specific outcomes that a decision maker would like to achieve if a disruption occurs. Since these attributes are very diverse and have different units, value functions can be used to assess the contribution of each attribute toward the overall resilience.

CHAPTER 1. INTRODUCTION

The current decade has seen several major disasters as Hurricane Maria and Hurricane Harvey, the Camp Fire in Paradise California, and the 2016 blizzard in eastern United States ("Snowzilla"). The frequency and the cost of these major disasters seem to be increasing. Disasters are uncertain, and it may be impossible to identify and prepare for every possible disaster scenario. Even if communities have prepared for specific disaster scenarios, each disaster behaves differently and can lead to deadly consequences and large financial costs, among other serious consequences. Increasing the resilience of communities can help these communities and their residents, neighborhoods, infrastructure systems, economies, and government services withstand and recover from disruptive events.

Resilience has been applied to many different disciplines, including ecology, infrastructure, business, and economic systems. One area of research into resilience focuses on the resilience of communities to disasters. Community resilience, also known as disaster resilience, is most commonly defined as a measure of the sustained ability of a community to utilize available resources to respond to, withstand, and recover from adverse situations (National Academies, 2012). At the state, county, and community level, resilience is increasingly becoming part of the emergency preparedness planning. Conceptualizing community resilience is important for local policymakers because they need to determine where to allocate resources for emergency preparedness and how best to plan for emergencies such that their communities will be more resilient to disasters. Having good methods to assess community resilience can be very helpful to inform those decision makers. Numerous studies, from perspectives of both social sciences and engineering, have attempted to assess and measure community resilience.

Perhaps the most common way to assess community resilience is by selecting dozens of indicators that are typically categorized into several dimensions. These indicators may be aggregated into a single number, a community resilience index. A community resilience index can be compared among different communities or counties to understand which geographic areas are more or less resilient to disasters. These indicators often are metrics for which data can be collected relatively easy (e.g., census data) although some resilience indices require surveys of residents.

A common feature of virtually all of these indicators or metrics for community resilience is that these indicators are inputs or characteristics of a community. For example, metrics might describe the socioeconomic status of community residents, the degree of home ownership, the number of civic or religious organizations within a community, or the size and revenue of businesses. The logical reasoning is that these inputs or characteristics of the community help explain or predict how well a community will fare during a disaster and how quickly it will recover after the disaster. Some studies have investigated if these indicators and indices are correlated with outcomes from a disaster such as property damage and fatalities. However, in order to truly measure community resilience, it may be better to actually assess what is meant by the term resilience, namely the ability of the community to withstand and recover from a disruption. Measuring the outputs or outcomes from disasters rather than assessing inputs that may or may not have a strong relationship to those outcomes may be a more appropriate assessment procedure.

Indicators currently suggested as assessments of community resilience seem to be selected in part because they are easier to measure than the outcomes from a disaster. Data are often publicly available for these indicators. However, the availability of data should not be confused with the usefulness of that data for accurately describing resilience.

Very little evidence exists in the literature that the proposed community resilience indices provide useful guidance for how a community should conduct emergency preparedness and planning. For example, if one of the indicators to assess community resilience is the percentage of residents with a high school diploma [3], should government officials attempt to increase the number of high school graduates in order to make their communities more resilient to disasters? Although increasing the number of high school graduates will likely have positive benefits for the community, it is not at all clear that such a strategy should be part of emergency preparedness and planning.

This thesis seeks to address some of these problems with many of the current methods for assessing community resilience by proposing a new approach to assess community resilience. This approach follows the principles of value-focused thinking, a popular method to analyze decision problems with multiple objectives. Our method to assess community resilience requires community leaders to identify fundamental objectives or outcomes that they want to achieve if a disaster occurs. Based on extensive research into the disaster literature and through conversations with some government officials, we propose dozens of outcome-focused objectives. By focusing on outcomes, we can be more confident that a value-focused thinking approach to community resilience actually captures elements that comprise and define community resilience. The value-focused thinking approach to community resilience can also serve as a method to help policymakers understand and compare the benefits of different alternatives for emergency preparedness. Thus, we believe the approach outlined in this thesis can do a better job of providing more meaningful decision support for allocating resources to enhance resilience.

The rest of the thesis is as follows. Chapter 2 reviews previous research efforts that present various indices and methods to measure community resilience. Chapter 3 presents our method to measure community resilience, which applies the principles of value focused thinking. Chapter 4 presents methods for operationalizing the objectives that were determined in chapter 3. Finally, chapter 5 presents the conclusion of this thesis.

CHAPTER 2. REVIEW OF LITERATURE

Resilience and social vulnerability indices can be used to help compare the vulnerability and resilience of different communities to disasters [1, 2, 4, 8, 22]. Cutter [3] reviews 27 different disaster or community resilience assessment procedures and identifies common elements among these indices. She finds that the assessments of resilience can be categorized into community capacities (social capacity, community functions, and planning) or assets (economic, social, environmental, and infrastructure). Cutter et al. [2] propose a disaster resilience index comprised of five dimensions: social resilience, economic resilience, institutional resilience, infrastructure resilience, and community capital. This disaster resilience index is applied to measure the resilience in 736 counties in the southeast United States.

The Community Disaster Resilience Index (CDRI) [13] uses the concept of capitals to define and measure resilience. Capital assets are the inherent capacities that a community or a region has at its disposal to deal with disasters. The CDRI incorporates 75 different indicators, categorized into social capital, economic capital, physical capital, and human capital. The CDRI is applied to counties in the Gulf Coast. The Resilience Capacity Index (RCI) measures the resilience capacity, or the pre-disaster resilience level as an indicator of the potential performance of a location under stress [14]. An economic resilience index [89] proposes that four major determinants (microeconomic stability, microeconomic market efficiency, good governance, and social development) can help predict how resilient a nation's economy will be a to a severe economic shock.

Resilience indices or community resilience assessments typically identify several metrics or indicators within each dimension, capacities, or function. Metrics are usually selected because they describe how prepared a community or county is, or they describe the inherent capacity of institutions, societies, or the residents within a community that should help the community withstand or recover from a disruption. For example, the "percent of population not speaking English as a second language" measures language competency of residents, which should help the social resilience of a community; the "ratio of large to small businesses" describes the economic resilience of a community; and "participation in in hazard reduction programs" is a metric for the institutional capacity of a community [1, 2]. The metrics are frequently normalized and then assigned weights in order to aggregate them into a single number, a single measure of resilience.

Many resilience and vulnerabilities indices are constructed and measured at the county level because census data exist at the county level; however, Arup et al. [9] and Spaans and Waterhout [10] introduce and discuss the city resilience framework. The resilience of cities is assessed along four categories: the health and well being of residents, infrastructure and the environment, economy and society, and leadership and strategy. These categories can be divided into twelve key indicators, and each indicator can be assessed according to seven qualities (e.g., robust, redundant, flexible, integrated). The resilience of the city of Rotterdam is examined as an application within this framework, but the analysis is primarily qualitative as opposed to quantitative [10].

Longstaff et al. [7] propose to assess community resilience as a function of resource robustness and adaptive capacity. Resource robustness refers to the availability and diversity of community's resources that could be used in the midst of a disruption. Adaptive capacity is more intangible and refers to a community's collective experience and memory and the community's connectedness, which the authors argue are important components to help a community withstand and recover from a disruption. The authors provide a list of questions to help a community assess its performance along these two dimensions.

Some researchers have questioned the appropriateness of indicators to measure community resilience or vulnerability. Socioeconomic indicators rely on census that may quickly become outdated [5]. A metric may be included as an indicator because data for that metric are readily available and not necessarily because the metric accurately describes vulnerability or resilience. Aggregating indicators that measure completely different things may not be appropriate and may average or hide important extremes within these indicators [25]. Methods for selecting indicators, collecting data for these indicators, and weighting and aggregating these indicators into an index number may be so fraught with errors and uncertainties that policy makers should be very leery of using these indices for making decisions and allocating resources [24].

Relatively little work has focused on whether these measures of resilience correlate with the actual consequences a community experiences during and after a disaster. The results of these validation studies suggest these resilience assessments are generally negatively correlated with negative outcomes from disasters (e.g., deaths, property damage), but the results are also very mixed with significant variability. Aggregated scores for typical resilience dimensions (social, economic, infrastructure, community capacity, institutional, and environmental) were found to be statistically significant in predicting the recovery of communities after Hurricane Katrina, but the effects were very small [23]. More resilient Gulf Coast communities as measured by the CDRI experience less property damage and have fewer fatalities from floods but are also more likely to have more floods leading to fatalities [13]. Bakkensen et al. [12] attempt to statistically validate three resilience indices and two vulnerability indices according to the three outcomes: property damage, fatalities, and frequency of disaster declarations. Two resilience indices and both vulnerability indices have predictive power for two of the three outcome metrics, but none have predictive power for all three outcomes. The third resilience index is statistically significant in predicting property damages and disaster declarations but in the wrong direction. In other words, more resilient communities, as measured by this third resilience index, experience greater property damages and more disasters. Statistical tests have also been performed for social vulnerability indices [26] and to quantify the relationship between social indicators and economic costs of disasters [6].

Another approach to assessing and measuring resilience appears in the engineering, infrastructure, and business literature [18, 100]. The foundational concept for many of these resilience assessments is the "resilience triangle" which measures resilience according to a sudden decrease in performance due to a disruptive event and the time after the event until recovery [16]. Enhancing resilience is measured by decreasing the area of the triangle formed by the system's performance function over time [97]. A variety of extensions to this basic concept have been proposed, including non-linear recovery [8], probabilistic assessments of resilience curves [98], time-dependent resilience

[99]. Community resilience could theoretically be measured in a similar manner to these metrics for infrastructure and engineering resilience [8], but measuring and even defining a community's performance before, during, and after a disruption is extremely challenging. Infrastructure performance is much easier to assess. For example, the number of customers without electricity is a clear metric to assess the performance of the electric power infrastructure during the time of a disruptive event.

This thesis addresses these deficiencies with many of the current metrics and indices for community resilience. This thesis borrows from the existing literature on community resilience and infrastructure resilience to propose a different way to measure and assess community resilience through a value-focused thinking (VFT) approach. VFT was developed specifically to help a decision maker select the best alternative for a multi-criteria decision problem [90]. VFT requires a decision maker to focus first on his or her values and objectives that he or she wants to achieve with a decision. VFT has been used to identify strategic objectives for an electric power utility [91], identify objectives and quantify the effectiveness of homeland security strategies [19], achieve consensus on decisions regarding the environment [91], and to assist communities in their planning [92, 93]. To the authors' knowledge, a VFT approach has not yet been applied to assessing or measuring community resilience.

Community resilience indices or measures are typically labeled as indicators because they are combinations of individual variables that represent different dimensions of community resilience. Since the value-focused thinking approach also aggregates many variables, the approach presented in this thesis could also be called an indicator. We prefer the term metric to emphasize that we are seeking to measure community resilience. However, we do not intend to make a distinction between the use of the term indicator and metric.

CHAPTER 3. A VALUE-FOCUSED THINKING APPROACH TO MEASURING COMMUNITY RESILIENCE

Many of the proposed resilience indices and metrics contain variables that are fairly easy to measure, such as the percentage of females in the labor force. These variables may not accurately describe what state and local government officials truly care about when they consider the resilience of their communities to severe disruptions and natural disasters. This thesis proposes to measure and assess community resilience by following VFT, which encourages decision makers to identify their fundamental objectives and attributes that define those fundamental objectives. VFT can broadly be divided into three activities: (i) identifying and structuring objectives, (ii) determining value functions for individual attributes, and (iii) assessing trade-off weights among the objectives and attributes [21].

A VFT approach helps form a very clear picture of the decision maker's objectives and priorities. The first activity of VFT, identifying and structuring objectives, frequently results in an objectives hierarchy. An objectives hierarchy begins with a single objective, which in this case is to maximize community resilience. That objective is decomposed into multiple fundamental objectives. Each of these fundamental objectives is further decomposed into sub-objectives, and this process continues until the bottom level of the objectives hierarchy consists of measurable attributes or metrics. 19 An objectives hierarchy thus helps create a clear path towards achieving the decision maker's objectives. VFT with identification of multiple objectives, formulation of value functions and assignment of weights has been effectively applied and demonstrated in the context of energy and homeland security [15, 20, 21].

This thesis uses an objectives hierarchy to identify measurable attributes that contribute towards a community's fundamental objective of maximizing its resilience. For VFT to be effective, each attribute at the bottom level of the objectives hierarchy must have a measurable quantity associated with it. Using an objectives hierarchy fulfills two purposes: (i) eliminates the vagueness of community resilience, and (ii) provides information about the decision makers' real objectives (i.e., what they really are concerned about in the context of a disaster).

Community resilience generally relates to a community's ability to withstand, adapt to, and recover from disruptions. Our approach identifies six fundamental objectives for community resilience: (i) maximize social resilience, (ii) maximize economic resilience, (iii) maximize infrastructure resilience, (iv) maximize environmental resilience, (v) maximize availability and use of resources, and (vi) maximize post-disaster functionality of critical services. These six fundamental objectives are similar to the broad categories or capacities that many researchers have proposed to measure community resilience. The unique element about this thesis is that the attributes that are used to measure each of these six fundamental objectives are comprised of outcomes rather than inputs or characteristics of the community.

3.1 Social resilience

Social resilience is defined by a disruption's impacts on community residents. A community exists to benefit its residents, and community leaders want to protect and make sure those residents are resilient to disruptive events. Every measure of community or disaster resilience that we know of incudes metrics related to residents of a community. As depicted in Table 1, social resilience in this thesis is decomposed into three components: (i) socially vulnerable (SV) residents, (ii) non-SV residents, and (iii) psychological resilience. As will be explained in the following paragraph, each of these three components are further broken down into metrics or measurable attributes. These attributes focus on the outcomes or consequences of a disaster because community leaders will be most interested in gaining insight into how disasters will affect these metrics. Although the list of attributes is designed to capture the most important elements of social resilience, community leaders may identify other elements or metrics of social resilience about which they are concerned.

Table 3.1: Attributes to measure social resilience

1. Social resilience
1.1 Socially vulnerable (SV) residents
1.1.1 Minimize fatalities
1.1.2 Minimize injuries
1.1.3 Minimize number of displaced residents
1.1.4 Maximize number of displaced residents who find new housing
1.2. Non-SV residents
1.2.1 Minimize fatalities
1.2.2 Minimize injuries
1.2.3 Minimize number of displaced residents
1.2.4 Maximize number of displaced residents who find new housing
1.3 Psychological resilience
1.3.1 Minimize residents' fear
1.3.2 Minimize symptoms of post-traumatic stress disorder
1.3.3 Minimize personal disruption of lifestyle
1.3.4 Minimize inconvenience to residents

A community's SV residents (e.g., lower income groups, racial minorities, the elderly) often suffer disproportionately from disruptions [27]. In light of this information, we separate the social resilience of SV residents from the social resilience of non-SV residents. This distinction allows community leaders to focus on the most vulnerable residents and those people who are most likely to be harmed by a disruption while also tracking metrics corresponding to the majority, or the non-SV, proportion of the community.

The attributes for both SV and non-SV residents of a community consist of fatalities, injuries, displaced residents, and residents who find new housing. Jonkman et al. [30] provide a model to estimate fatalities from small-probability, large-consequence events. This model could be used by communities to forecast the number of fatalities that may occur from a disruptive event. The model combines the system characteristics, physical effects, evacuation models, the number of people at risk, and a dose-response function to estimate the loss of life.

Even if residents' lives are spared and they are uninjured, they require adequate housing and shelter. Thus, the components for SV residents and for non-SV events each include two attributes for housing: (i) minimizing the number of residents displaced from their homes and (ii) maximizing the number of displaced residents who find new housing. The ideal for a community during a disruption would be that no residents are displaced from their houses. However, since that ideal is often unattainable, communities will desire that those displaced residents have adequate housing and shelter. This could be because some residents stay with friends or family, the community establishes large shelters for displaced people to stay, and the government provides individual shelters (e.g., mobile trailers) for residents who have lost housing. Frameworks and models have been proposed to integrate different scientific perspectives into post-disaster decision making and housing recovery for SV residents [28].

Large-scale disruptions can have lasting effects on the social cohesion of a community [29], and the psychology of residents plays a very important role in averting further losses and in recovery efforts. Residents' sentiments toward their community provide predictive power in determining psychological resilience to hazards such as toxic waste, salinity, and volcanoes. An individual's socioeconomic disadvantage, which could be driven by race, unemployment, or economic status, are associated with a greater likelihood of psychiatric disorder. Thus, the third component under social resilience is the psychological resilience of community residents.

Psychological resilience will probably be most important for intentional incidents such as a terrorist attack or a mass shooting, but it may also be important for recovery from natural disasters. From the psychological literature, adult resilience can be defined as the ability of adults who are exposed to a traumatic or highly disruptive event to maintain a relatively healthy functioning of their psychological, emotional, and physical states [96]. Much of the most recent literature on psychological resilience has focused on the psychological impacts from the September 11 terrorist attacks although some research on the psychological resilience to Hurricane Sandy has been conducted, as well as children's ability to cope with flooding after Hurricane Floyd.

Our framework proposes four attributes to measure psychological resilience: fear, post-traumatic stress disorder, disruption to lifestyle, and inconvenience. In their objective hierarchy for homeland security, Keeney and von Winterfelt [31] propose that fear, disruption to lifestyle, and inconvenience are three attributes that can be used to assess the social impacts of decision making for homeland security. The objectives hierarchy presented here borrows the same attributes because they are also important for determining how to make a community more resilient to disruptive events. Surveying residents could provide a means to measure these attributes. A Fear of Terrorism Scale is based on survey respondents' answers to a score of questions. Medical research has used a fear of death scale in order to assess individuals' attitudes toward rare illnesses and has been extended to terrorist attacks. Post-traumatic stress syndrome, depression, and substance abuse can all be indicators or metrics of psychological resilience (or the lack of resilience).

3.2 Economic resilience

The economy of a community is vital to its survival. In order to ensure the survival and good health of a community, it is important to protect the economy from the adverse consequences of the disaster. Increasing the economy's resilience helps protect the economy from damage and enables the economy to recover more quickly. Rose [42] quantifies economic resilience in two different ways. Static resilience measures the difference between the estimated percent change in economic output and the maximum percent change in total output. Dynamic resilience is measured as the gain in economic output achieved by better repair, reconstruction, and recovery activities. In line with previous work, the metrics in this section aim to capture impact of a disruption on the economy and recovery of the economy.

Economic losses are frequently divided into direct losses (including the cost of damaged and destroyed buildings and the loss of industrial functions) and the indirect losses (second and third-order effects that are induced by the direct losses). The hierarchy for economic resilience (Table 2) includes a metric in order to address direct losses. Direct losses typically include the cost of infrastructure damage, debris removal and reconstruction. However, indirect losses include cascading losses as a result of direct losses, infrastructure damage and loss of functionality which in turn lead to business, workforce, and income losses.

Table 3.2: Attributes to measure economic resilience

2. Economic resilience
    - 2.1 Minimize direct losses ($)
    - 2.2 Business resilience
        - 2.2.1 Minimize number of business closures
        - 2.2.2 Minimize length of time of business closures
        - 2.2.3 Minimize number of businesses that cannot reopen
    - 2.3 Workforce resilience
        - 2.3.1 Minimize number of residents who cannot find jobs or work again
        - 2.3.2 Minimize time that residents cannot find work
        - 2.3.3 Minimize number of available jobs that cannot find suitable employees
        - 2.3.4 Minimize time until available jobs are filled
    - 2.4 Income losses
        - 2.4.1 Minimize income losses of SV residents
        - 2.4.2 Minimize income losses of non-SV residents
        - 2.4.3 Minimize residential losses that are not insured

Many models used to measure losses, such as the input-output model, the social accounting matrix, and the computable general equilibrium model have evolved to incorporate disaster-specific factors [32]. One approach used to measure the economic impacts is by using a dynamic inoperability input output model (IIM). Many studies have tailored the IIM to suit specific scenarios

[35-37]. In a non-IIM approach, Hallegate [33] attempted to estimate the impacts of a natural disaster on the supply chain using an ARIO inventory model. There are also methods to estimate the impact of a disaster induced supply chain constraint where input-output models are not applicable [34]. Martinelli et al. [41] provide a framework based on HAZUS to assess the economic impact of natural disasters.

Since the health of an economy is dependent on the financial health of both enterprises and residents, business resilience and income losses attempt to capture the effects of the event on businesses and residents, respectively. Business resilience focuses on the post-disaster operations or closures of businesses and on how the disaster has affected the workforce availability.

Surveys of business after a disaster can provide insight into how business are impacted by the event and on their speed and effectiveness of recovery. Zobel [44] applies the infrastructure resilience of Bruneau et al. [45] to quantify the resilience of businesses and organizations. He measures the resilience of business based on lost performance and the time to recover to full performance. Similarly, the number of business that close and the length of time that it takes them to reopen are the metrics in this thesis used to measure business resilience. The number of permanently closed businesses are also addressed in the hierarchy.

Most of the studies cited in the previous paragraphs focus on the economic impact of a disruption, but significant research has also modeled economic recovery. Webb et al. [39] argue that long-term recovery of businesses is affected by various firm characteristics, including the prevailing market conditions, physical damage and disruption of operations. Porter [40] argues that regional economies impacted by the Deepwater Horizon oil spill would recover more slowly because of the global economic recession. Stock markets have been shown to be resilient to shocks caused by earthquakes [38].

Income losses address the financial effects of the disaster on community residents. It considers many different sources of income like wages and rent. Some disasters may have minimal impact on total employment, but there can be significant drops in personal income [43]. This category has been further divided into income losses for SV and non-SV residents to focus attention that

SV residents may suffer more from income losses than non-SV residents. Workforce resilience is measured as the number of people that are out of work and the time it takes for people to resume working. Workforce resilience also includes the loss of employees and the time it takes for businesses to find new employees.

3.3 Infrastructure resilience

The failure of infrastructure systems can cripple a community. Infrastructure systems may be very vulnerable to damage during natural disasters. To ensure a functioning community, it is important to protect these systems and to repair any damages quickly. We address the resilience of infrastructure systems in terms of the damage sustained by the systems i.e. impact and the time and effort required for their restoration i.e. recovery. Since the failures of infrastructure systems will be mostly due to physical damage, the impacts are measured as such and the time for recovery is measured in days. As depicted in Table 3, infrastructure resilience is comprised of debris management, critical infrastructure resilience, and non-critical infrastructure resilience. These three categories of resilience will be further decomposed into their respective components.

The resilience of infrastructure systems is a popular topic for researchers in engineering. Some studies have proposed resilience indices specifically for infrastructure systems. Fischer et al.'s [47] resilience index (RI), ranging from 0 to 100, is derived from three categories: robustness, resourcefulness, and recovery. The IIM, network models, and "fragility" functions have all been proposed to assess resilience [48, 49]. Many frameworks assess the resilience of infrastructure systems in terms of two dimensions: robustness (ability to withstand impact) and rapidity (time to recovery) [50].

Post-disaster debris can cause further accidents and damage and will generally be an obstacle to recovery efforts [62]. Removing debris is necessary to facilitate the recovery of the affected region. The more quickly debris can be cleared, the more quickly the community can recover. This component is measured as the time taken to clear debris. Debris can be estimated based on the type of debris (e.g., structural, trees, sediment, mixed), the location, and volume of the structure

[63]. Simulation can be used to model the time to remove debris based on the expected volume and the ability of debris management services.

The criticality of infrastructure components depends on which sets are damaged or destroyed by a disruption [46]. Table 3 depicts four critical infrastructures: transportation, energy, communication systems, and waste management. These seem to be the most critical because of the amount of attention and focus that disaster researchers have spent studying these systems. Water infrastructure could be another critical infrastructure system, but that is included in the hierarchy for resource resilience.

Table 3.3: Attributes to measure infrastructure resilience

3. Infrastructure resilience

  3.1 Minimize time to clear debris and remove damaged buildings and infrastructure

  3.2 Critical infrastructure resilience

    3.2.1 Transportation resilience

      3.2.1.1 Highway and road resilience

        3.2.1.1.1 Minimize miles of highway and road closures

        3.2.1.1.2 Minimize time that highways and roads are closed

      3.2.1.2 Airport resilience

        3.2.1.2.1 Minimize number of cancelled flights

        3.2.1.2.2 Minimize time to recovery of normal airport operations

      3.2.1.3 Waterway resilience

        3.2.1.3.1 Minimize number or percentage of waterway port closures

        3.2.1.3.2 Minimize time until ports reopen or return to full operations

    3.2.2 Energy resilience

      3.2.2.1 Electricity resilience

        3.2.2.1.1 Minimize number of residential homes without electricity

        3.2.2.1.2 Minimize time that residential homes do not have electricity

Table 3.3 (continued)

3.2.2.2.3 Minimize number of commercial buildings without electricity
3.2.2.2.4 Minimize time that commercial buildings to not have electricity
3.2.2.2 Gas resilience
3.2.2.2.1 Minimize number of residential homes without gas
3.2.2.2.2 Minimize time that residential homes do not have gas
3.2.2.2.3 Minimize number of commercial buildings without gas
3.2.2.2.4 Minimize time that commercial buildings do not have gas
3.2.2.3 Maximize availability of fuel (i.e. gasoline)
3.2.3 Communications and information technology resilience
3.2.3.1 Minimize number of telephone lines or poles damaged
3.2.3.2 Minimize time to repair telephone lines or poles
3.2.3.3 Minimize number of people who lose Internet connectivity
3.2.3.4 Minimize time to restore Internet connectivity
3.2.4 Waste management resilience
3.2.4.1 Minimize sewage line closures
3.2.4.2 Minimize time to restore sewage line closures
3.3 Non-critical infrastructure resilience
3.3.1 Minimize number of destroyed houses
3.3.2 Minimize time to replace destroyed houses
3.3.3 Minimize number of damaged homes
3.3.4 Minimize time to repair damage homes

Transportation resilience addresses three major modes of transportation: roadways, airways, and waterways. These transportation systems are very important for recovery efforts since they can be used for evacuations as well as to bring in additional resources. The impacts and recovery of these systems rely on metrics that are appropriate for the mode of transport. For example, the impact on roadways is measured by the number of road closures, and the impact of airways is measured by the number of cancelled flights. The wealth of studies that analyze the effects of disruptions on transportation systems reinforces their importance towards the functioning of a community, and why it is important to include them in studies regarding resilience.

A common approach to enhance resilience of transportation networks is the usage of stochastic modeling or stochastic programming or their variants [51-54]. Many studies measure the impacts on supply chain caused by the physical damage to transportation systems [55-56]. Transportation disruptions can also lead to significant business interruption losses [57]. Chang and Nojima evaluate the post-disaster performance of Kobe city's transportation network in terms of network coverage and transport accessibility [58]. These types of studies can be used to understand how a community's transportation system might be impacted by different types of disruptive events.

To account for the different forms of energy available to a community resident, energy resilience is decomposed into electricity resilience, gas resilience, and fuel resilience. The attributes consist of the impacts and recovery time for both residential customers and business customers. Research in energy resilience approximate the impact of disruptions on energy supply. MacKenzie and Barker [59] provide a data-driven approach to derive a resilience parameter through regression models with electric power outage data. Spatial generalized linear mixed modeling applied to grid cells in a region can be used to predict the number of outages likely to occur as a result of storms [60]. Damage to the electric power system due to hurricanes can be assessed by modeling the expected damage to electric poles [61].

Communication, in some form, is an important component of most if not all community resilience models [11, 69]. Communication systems and resources represent the reservoirs in which community meaning-making, information exchange, interactions, and connections can occur [67]. Communication technologies are extremely important in mitigating and preventing disasters [65]. Communication and information systems are also important for coordination operations during and after the disaster. The objectives hierarchy focuses on telephone poles and Internet connectivity. Damage to communication networks can be assessed through field collected data and information and by garnering availability [66]. In the hierarchy, communication resilience seeks to minimize impacts and minimize recovery time for Internet systems and telephone poles.

The resilience of waste management capabilities is measured by the impact and recovery of sewage lines in the affected region. Basic sanitation facilities and access to basic hygiene may be unavailable or worsen due to natural disasters [71]. Waste that is not properly managed are a serious health hazard and can further the spread of infectious diseases [70].

Non-critical infrastructure is also addressed in the hierarchy because it impacts the quality of life of community residents. Non-critical infrastructure resilience aims to capture the concerns the decision maker may have about the residents' personal immovable property such as their homes. The hierarchy addresses this concern by including objectives that aim to minimize the number of destroyed and damaged homes and the time it takes for these homes to be habitable again.

3.4 Environmental resilience

Disruptions - whether caused by humans or by nature - can also damage the environment. The specific attributes that measure the environment are likely very geographic-specific. However, some simple attributes that are applicable to a wide range of communities and locations are the geographic area of natural habitat, the number of animals impacted, and pollution.

Damage to the environment can often lead to the extinction or exodus of different plants and animals that could be crucial to the local ecosystem. Significant biomass decline facilitated by tree mortality and tree injury is one of the immediate effects of an earthquake [72]. The 2004 Indian ocean tsunami lead to changes and uprooting in the mangrove population due to seawater inundation [73]. The resilience framework presented in Table 4 assesses environmental impacts as the acreage of the habitat destroyed and the time for the habitat to recover. The recovery of habitats may be very different compared to other recoveries. Habitats sometimes take decades to recover to a pre-disaster state. The habitat may never be restored to its pre-disruption state. In such cases, recovery can be measured as the time until the community adapts to the "new" habitat.

Table 4 also includes the impacts on individual animals. These animals can be further categorized into species depending upon their importance in maintaining the ecosystem balance.

Table 3.4: Attributes to measure environmental resilience

4. Environmental resilience
4.1 Minimize square miles of habitat destroyed
4.2 Minimize time until habitat is restored
4.3 Minimize number of animals impacted (could be categorized according to species)
4.4 Pollution
4.4.1 Minimize pollution in air
4.4.2 Minimize pollution in water
4.4.3 Minimize pollution in soil

The impacts on the environment such as pollution should be measured in appropriate units such as parts per million for air and water pollution. Forest fires and fires from earthquakes and volcanic eruptions pollute the air and water. Volcanic eruptions are notorious for emitting vast quantities of polluting gases and ash resulting in global temperature changes [74, 75]. Floods can contaminate the soil and even saturate it with water. Given the importance of soil fertility and stability to agriculture and to construction projects, minimizing soil pollution is included as one of the objectives in environmental resilience.

3.5 Resource resilience

Resources include consumables like food and water and the sources of these consumables such as agriculture and livestock. Resource resilience (Table 5) is decomposed in order to address agriculture, food, and potable water. Agriculture resilience is further decomposed into metrics that measure the yield lost as a result of the disruption and the time taken to restore the pre-disruption state of agricultural yield. Agriculture resilience also aims to minimize the loss of livestock. If the disruption impacts a rural area where agriculture is a major component of the community, the impact and time to recovery of agriculture may be very important to assess community resilience. If the region is urban, the decision maker may not place much importance on agricultural resilience and can choose to focus more on food resilience. Resource shortages also lead to broader economic consequences over a period of time [78].

Table 3.5: Attributes to measure resource resilience

5. Resource resilience
5.1 Agricultural resilience
5.1.1 Minimize agricultural yield loss
5.1.2 Minimize time to recover agricultural loss (e.g. harvest cycles)
5.1.3 Minimize loss of livestock
5.2 Food resilience
5.2.1 Minimize number of people without sufficient food
5.2.2 Minimize time until food shortage ends
5.3 Maximize availability of potable water

Resource resilience aims to minimize food shortages. Food resilience is measured in terms of amount of food shortage and the time it takes to end the shortage. Israel and Briones' [79] study in the Philippines found that typhoons negatively impact paddy rice production and the food security of the households in the affected areas. Tropical cyclones, floods, and droughts can also substantially impact natural resources. Natural disasters can affect multiple dimensions of food security such as the availability of supplies, access to food, and utilization. People in remote areas often suffer disproportionally from significant shortfalls in food availability [81].

Given the importance of potable water to sustenance of human life and activity, resource resilience also seeks to maximize the availability of potable water to community residents. Aubuchon and Morley [80] assess the monetary benefit of continuing to provide water after a disruptive event to both businesses and residents. Luna et al. [77] use colored Petri nets to simulate the behavior and restoration process of a water distribution network in Tokyo following an earthquake. Water supply networks may also be vulnerable to physical attacks [76].

3.6 Post-disaster functionality of critical services

Emergency services are critically important to mitigate the effects of a disruption. However, the services themselves can also be susceptible to the effects of a disruption either because the disruption directly affects these services or because the services' capabilities are overstretched by the disruption. The objectives hierarchy (Table 6) includes the ability of the medical, police, fire, educational, and social services to continue to provide necessary functions during and after a disaster.

Table 3.6: Attributes to measure functionality of critical services

6. Post-disaster functionality of critical services
6.1 Medical services
6.1.1 Maximize ratio of post-disruption capability to pre-disruption capability
6.2 Police services
6.2.1 Maximize number of law enforcement officers available post-disruption
6.3 Fire management services
6.3.1 Maximize number of firefighters available post-disruption
6.4 Education services
6.4.1 Maximize number of schools open post-disaster
6.4.2 Minimize amount of time until all schools are reopened
6.4.3 Maximize number of students who attend schools
6.5 Social, safety-net services
6.5.1 Maximize number of employees working in social, safety-net services

The functionality of medical services can be assessed as a percentage of the pre-disaster condition. Medical services must consider the availability of both personnel and emergency medical equipment for considerably high emergency patient traffic. Hospital emergency departments throughout the United States are severely crowded, which raises concerns about their ability to respond to mass casualty or volume surges [82]. Many medical facilities that would need to respond to a disaster might have inadequate disaster plans [94, 95]. Medical facilities can also be damaged by the disruptive event, which can lead to the loss of vital services, as occurred during the 1994 Northridge earthquake [83].

The functionality of the police and fire departments can be measured based on the number of available personnel after the disaster. The personnel and equipment of these services can be physically impacted by the disruption, reducing their effectiveness, and potentially rendering them ineffective. Emergency workers pressed into service during times of crisis are seriously affected by the emergency work [86]. According to surveys, emergency personnel may not participate equally in the response to different threats [87].

Education plays a central role in a community. Apart from being centers of learning, they routinely serve as designated shelters during a disruption [84]. Disruptions can negatively impact the educational function of schools because they mentally affect students and cause disturbances in coursework [85]. It is the interest of students, their families, and the community to restore schools' functioning as soon as possible.

For residents who are unable to work or unable to support themselves, a natural disaster makes matters much worse. Social safety nets are an absolute necessity for such residents. Another metric of resilience is the functioning of safety net services as they offer social protection and social risk management, thereby reducing impact and aiding in recovery [88].

CHAPTER 4. OPERATIONALIZING OBJECTIVES FOR COMMUNITY RESILIENCE

Perhaps the biggest challenge with using this objectives hierarchy and these attributes to assess community resilience is the difficulty in assigning a number for each attribute, especially prior to a disruption. A community could assess many of these attributes after a disruption occurs. However, since a resilience index and associated metrics should be able inform decision making, state and local government officials need to be able to assess a community's resilience before a disruption and understand how resilience can be enhanced through emergency preparedness.

Modeling and analytical tools can help a community assign numbers to these attributes. Data from previous disruptions -both disruptions experienced by the community and disruptions in other locations that resemble those that the community might experience - could be used to assess each attribute. Simulation provides a powerful method to understand the impacts of different types of disruptions with varying degrees of severity. As cited in the chapter describing the attributes for each objective, mathematical models have been proposed to describe how disruptions impact the performance of specific systems (e.g., transportation infrastructure, economic activity). Assigning probability distributions can quantify the uncertainty that usually exists in each of these attributes.

Until now, the discussion has centered around the first step of VFT, identifying and structuring objectives. We defined objectives and the metrics that measure progress towards the objectives. In order evaluate and compare among alternatives to enhance community resilience, VFT recommends combining all of the attributes into a single number through a multi-attribute value function. A multi-attribute value function frequently relies on individual value functions over the attributes. The individual value function provides a way to scale the level of metrics from a numerical value in its own units to a real number between 0 and 1. Value functions make it easier to compare and aggregate metrics that have different units.

Value functions are preferable to just normalizing an attribute because value functions incorporate the decision maker's preferences about the attribute. A linear value function - which is similar to normalizing the attribute - means the value or usefulness of an attribute increases or decreases linearly with respect to the metric for the attribute. Concave value functions are used for attributes with diminishing marginal returns and convex value functions for increasing marginal returns.

After the individual value functions have been determined and applied to calculate values for each individual attribute, the values can be aggregated to calculate a single number reflecting community resilience. In many multi-attribute decision problems, the type of function to aggregate these values is an additive value function. An additive value function is only justified if all of the attributes are mutually preferentially independent or value independent. Attributes are mutually preferential independent if an individual value function does not depend on the specific levels or trade-offs among the other attributes. If all the attributes are mutually preferentially independent, an additive value function can be used. Resilience R could be calculated:

$$R = \sum w_i v_i \tag{1}$$

where R is resilience, w_i is the trade-off weight corresponding to attribute i, and v_i is the value corresponding to attribute i.

Some attributes identified in the previous chapter are mutually preferential independent. For example, a decision maker's value function for the number of fatalities will likely remain the same whether many customers are without electric power or only a few customers are without power.

However, many of the components of resilience consist of an attribute describing the impact and another attribute describing recovery time. The attributes of impact and recovery time for a resilience component are not mutually preferentially independent. For example, if only a few customers are without electric power, a community decision maker's value function for recovery would likely be relatively constant over the days until full recovery. If many customers are without electric power, the decision maker's value function would likely be nonlinear because a decision maker would perceive a lot more value in full recovery in 1 day than in 30 days. The following value function v(impact,time) could be used to relate the impact and time until recovery:

$$v(impact, time) = k_{impact}v(impact) + k_{time}v(time) + (1 - k_{impact} - k_{time})v(impact)v(time) \quad (2)$$

where k_{impact} and k_{time} are weights on the importance of impact and time, respectively, $v(impact)$ is the individual value function for impact, and $v(time)$ is the individual value function for the time of recovery. The attributes impact and time can be considered as substitutes for each other, which means that $k_{impact} + k_{time} > 1$. The attributes are substitutes because if recovery can occur instantly (i.e., time = 0), then $v(impact, 0) = 1$ for any level of impact. Similarly, if there are no impacts (i.e., $impact = 0$), then $v(0, time) = 1$ for any level of recovery time.

Another approach can eliminate the use of independent value functions and their corresponding coefficients for the attributes impact and time. The resilience triangle, developed by Bruneau et al. [16], provides a method to use the product of the magnitude of impact and recovery time. Zobel [18] measures resilience as the area under the curve (i.e., the triangle) which is normalized by the maximum impact and the maximum time in order to ensure resilience is bounded between 0 and 1. Based on the concept of the resilience triangle, using the product of impact and recovery time in the value function seems appropriate:

$$v(impact, time) = 1 - \frac{impact * time}{impact_{max} * time_{max}} \quad (3)$$

where $impact_{max}$ is the maximum tolerable impact and $time_{max}$ is the maximum tolerable recovery time.

Uncertainty will exist with many and possibly all of the attributes presented in this thesis. Consequently, a multi-attribute utility function should be used in place of a multi-attribute value function. Value functions are designed to capture preferences when attributes are certain, but utility functions are used when attributes are uncertain in order to capture the risk attitude of the decision maker. Many of the equations presented above could be used with utility functions under certain assumptions. For example, an additive utility function similar to Equation (1) is appropriate if the attributes are additive independent, which is a more stringent condition than mutually preferential independent. Another approach is to calculate the multi-attribute value function and then to incorporate a decision maker's risk attitude over those values to construct a utility function.

It is beyond the scope of this thesis to aggregate these attributes into a value function or utility function. The specifics of the aggregation scheme including the individual value functions and the trade-off weights for each attribute will depend on the specific community. Decision analysis has provided numerous examples demonstrating how to derive value and utility functions and trade-off weights for a wide variety or private-sector and public-sector decision problems in which the problems contain scores of attributes. These same techniques can also be applied to help a community leader construct a resilience metric that aggregates the attributes in the objectives hierarchy.

CHAPTER 5. APPLICATION OF FRAMEWORK

This chapter demonstrates how the proposed framework can be used to make decisions. The example used is completely artificial and not based on any studies.

Consider a city approximately the size of Des Moines, Iowa. The leaders of the city are planning on making their community more resilient to disruptions. The city leadership needs to determine the best strategies to make their community better prepared and more resilient to disruptions. The city leaders are considering four alternatives, and these four alternatives are assessed using the attributes discussed in Chapter 3.

The rest of this chapter demonstrates how our framework can be used to determine the best strategy.

5.1 Value functions

First, the leadership's value function for each attribute should be established using the best case and worst case scenarios for each attribute. The value function is a reflection of how the decision maker thinks about each attribute.

This exercise results in value functions that are linear or exponential and value functions that are mutual dependent. Mutual dependent value functions are a combination of impact and recovery time.

$$v(impact, time) = 1 - \frac{impact * time}{impact_{max} * time_{max}} \tag{5.1}$$

where $impact_{max}$ is the maximum tolerable impact and $time_{max}$ is the maximum tolerable recovery time.

The city leadership's value functions are depicted in Tables 5.1 - 5.6.

Table 5.1: Value functions of social resilience attribute

Attribute	Units	Best case	Worst case	Value function
Fatalities (SV residents)	Count	0	150	Linear
Injuries (SV residents)	Count	0	1500	Linear
Displaced residents (SV)	% residents	0	25	Linear
New housing for displaced residents (SV)	% of displaced residents	100	0	Linear
Fatalities (non-SV residents)	Count	0	200	Linear
Injuries (non-SV residents)	Count	0	2500	Linear
Displaced residents (non-SV)	% residents	0	35	Linear
New housing for displaced residents (non-SV)	% of displaced residents	100	0	Linear
Residents' fear	% residents	0	75	Linear
Symptoms of PTSD	% residents	0	30	Linear
Personal disruption of lifestyle	% residents	0	100	Linear
Inconvenience to residents	% residents	0	100	Linear
Number of people who relocate from the community	% residents	0	20	Linear

Table 5.2: Value functions of economic resilience attributes

Attribute	Units	Best case	Worst case	Value function
Direct losses	Dollars	0	1,000,000,000	Exponential

Table 5.2 (continued)

Number of business closures	Count	0	300	Mut. dependent
Length of time of business closure	Days	0	180	
Number of permanent business closures	Count	0	200	Linear
Number of residents who cannot find jobs or work again	% residents	0	10	Linear
Number of residents who cannot find jobs	% residents	0	20	Linear
Number of available jobs that cannot find suitable employees	% of jobs	0	100	Mut. dependent
Time until available jobs are filled	Days	0	365	
Income losses of SV residents	Dollars	0	15,000,000	Linear
Income losses of non-SV residents	Dollars	0	100,000,000	Linear
Residential losses that are not insured	Dollars	0	200,000,000	Linear

Table 5.3: Value functions of infrastructure resilience attributes

Attribute	**Units**	**Best case**	**Worst case**	**Value function**
Time to clear debris	Days	0	30	Exponential

Table 5.3 (continued)

Miles of highway and road closures	Miles	0	80	Mut. dependent
Time for which highways and roads are closed	Days	0	30	
Number of cancelled flights	Count	0	100	Mut. dependent
Time to restore normal airport operations	Days	0	90	
Number of waterway port closures	% of ports	0	100	Mut. dependent
Time until ports return to full operations	Days	0	60	
Number of residential homes without electricity	Count	0	2000	Mut. dependent
Time that residential homes do not have electricity	Days	0	15	
Number of commercial buildings without electricity	Count	0	2500	Mut. dependent
Time that commercial buildings do not have electricity	Days	0	30	
Number of residential homes without gas	Count	0	3000	Mut. dependent
Time that residential homes do not have gas	Days	0	30	
Number of commercial buildings without gas	Count	0	5000	Mut. dependent
Time that commercial buildings do not have gas	Days	0	60	

Table 5.3 (continued)

Availability of fuel (gasoline)	% of operational gas stations	100	0	Linear
Number of telephone lines/poles damaged	Count	0	10,000	Mut. dependent
Time to repair telephone lines/poles	Days	0	180	
Number of people who lose internet connectivity	Count	0	500,000	Mut. dependent
Time to restore internet connectivity	Days	0	210	
Number of sewage line closures	Count	0	250	Mut. dependent
Time to restore sewage lines	Days	0	30	
Number of destroyed homes	Count	0	750	Mut. dependent
Time to replace destroyed homes	Days	0	1095	
Number of damaged homes	Count	0	5000	Mut. dependent
Time to repair damaged homes	Days	0	1825	

Table 5.4: Value functions of environmental resilience attributes

Attribute	**Units**	**Best case**	**Worst case**	**Value function**
Square miles of habitat destroyed	Sq. miles	0	250	Mut. dependent

Table 5.4 (continued)

Time until habitat is restored	Projected years	0	15	
Number of animals impacted	Count	0	7500	Linear
Pollution in air	Air quality index	150	0	Linear
Pollution in water	Water quality index	90	25	Linear
Pollution in soil	Soil Quality index	100	20	Linear

Table 5.5: Value functions for resource resilience attributes

Attribute	**Units**	**Best case**	**Worst case**	**Value function**
Agricultural yield loss	Tons	0	1,000,000	Mut. dependent
Time to recover agricultural yield loss	Number of harvest cycles	0	4	
Loss of livestock	Count of animals	0	250,000	Linear
Number of people without sufficient food	Count	0	150,000	Mut. dependent
Time until food shortage ends	Days	0	30	
Availability of potable water	% of residents with access to potable water	100	50	Exponential

Table 5.6: Value functions of post-disaster functionality of critical services

Attribute	Units	Best case	Worst case	Value function
Ratio of post-disruption capability to pre-disruption capability of medical services	Ratio	1	0.5	Linear
Number of law-enforcement officers available post-disruption	% of pre-disaster availability	100	50	Linear
Number of firefighters available post-disruption	% of pre-disaster availability	100	50	Linear
Number of schools open post-disaster	% of pre-disaster availability	100	50	Mut. dependent
Time until all schools are reopened	Days	0	60	
Number of students who attend schools	% of pre-disaster enrollment	100	30	Linear
Number of employees working in social, safety-net services	% of pre-disaster availability	100	50	Linear

5.2 Weights

Since we will use a weighted additive function to determine resilience, we must determine appropriate weights for each attribute's value function. Weights can be elicited from a decision maker using various methods, but in this application, swing weighting was used. The weights for each attribute is provided in Table 5.7.

Table 5.7: Attributes and their weights

Attribute	**Value function**	**Global weights**
Fatalities (SV residents)	Linear	0.0507
Injuries (SV residents)	Linear	0.0279
Displaced residents (SV)	Linear	0.0178
New housing for displaced residents (SV)	Linear	0.01015
Fatalities (non-SV residents)	Linear	0.0482
Injuries (non-SV residents)	Linear	0.0264
Displaced residents (non-SV)	Linear	0.0170
New housing for displaced residents (non-SV)	Linear	0.0096
Residents' fear	Linear	0.0123
Symptoms of PTSD	Linear	0.0136
Personal disruption of lifestyle	Linear	0.0035
Number of people who relocate from the community	Linear	0.0185
Inconvenience to residents	Linear	0.0027
Direct losses	Exponential	0.0692
Number of business closures Length of time of business closure	Mutual dependent	0.0142
Number of permanent business closures	Linear	0.0174
Number of residents who cannot find jobs or work again	Linear	0.0129
Number of residents who cannot find jobs	Linear	0.0082
Number of available jobs that cannot find suitable employees	Mutual dependent	0.0057

Table 5.7 (continued)

Time until available jobs are filled		
Income losses of SV residents	Linear	0.0093
Income losses of non-SV residents	Linear	0.0078
Residential losses that are not insured	Linear	0.0069
Time to clear debris	Exponential	0.0581
Miles of highway and road closures Time for which highways and roads are closed	Mutual dependent	0.0144
Number of cancelled flights Time to restore normal airport operations	Mutual dependent	0.0122
Number of waterway port closures Time until ports return to full operations	Mutual dependent	0.0057
Number of residential homes without electricity Time that residential homes do not have electricity	Mutual dependent	0.0087
Number of commercial buildings without electricity Time that commercial buildings do not have electricity	Mutual dependent	0.0080
Number of residential homes without gas Time that residential homes do not have gas	Mutual dependent	0.0066
Number of commercial buildings without gas Time that commercial buildings do not have gas	Mutual dependent	0.0050
Availability of fuel (gasoline)	Linear	0.0044
Number of telephone lines/poles damaged Time to repair telephone lines/poles	Mutual dependent	0.0104
Number of people who lose internet connectivity Time to restore internet connectivity	Mutual dependent	0.0121
Number of sewage line closures Time to restore sewage lines	Mutual dependent	0.0209
Number of destroyed homes Time to replace destroyed homes	Mutual dependent	0.0131
Number of damaged homes	Mutual dependent	0.0118

Table 5.7 (continued)

Time to repair damaged homes		
Square miles of habitat destroyed Time until habitat is restored	Mutual dependent	0.0195
Number of animals impacted	Linear	0.0184
Pollution in air	Linear	0.0112
Pollution in water	Linear	0.0101
Pollution in soil	Linear	0.0054
Agricultural yield loss Time to recover agricultural yield loss	Mutual dependent	0.0206
Loss of livestock	Linear	0.0152
Number of people without sufficient food Time until food shortage ends	Mutual dependent	0.0740
Availability of potable water	Exponential	0.0852
Ratio of post-disruption capability to pre-disruption capability of medical services	Linear	0.0354
Number of law-enforcement officers available post-disruption	Linear	0.0286
Number of firefighters available post-disruption	Linear	0.0327
Number of schools open post-disaster Time until all schools are reopened	Mutual dependent	0.0088
Number of students who attend schools	Linear	0.0074
Number of employees working in social, safety-net services	Linear	0.0258

5.3 Strategies to increase resilience

The city leadership is provided with four different strategies designed to increase their community's resilience. Each strategy places focus on different aspects of the community.

Strategy 1: This strategy focuses on social resilience and infrastructure resilience.

Strategy 2: This strategy focuses on social resilience, economic resilience and resource resilience.

Strategy 3: This strategy focuses on economic resilience and infrastructure resilience.

Strategy 4: This strategy focuses on social resilience and post-disaster functionality of critical services.

Each strategy's performance is depicted in Table 5.8.

Table 5.8: Strategies to increase community resilience

Attribute	**Units**	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**
Fatalities (SV residents)	Count	30	33	118	32
Injuries (SV residents)	Count	550	480	948	780
Displaced residents (SV)	% residents	6	6.8	12.3	13
New housing for displaced residents (SV)	% of displaced residents	85	87.2	75	93
Fatalities (non-SV residents)	Count	30	55	97	26
Injuries (non-SV residents)	Count	550	386	952	1200
Displaced residents (non-SV)	% residents	10	8.5	10	10
New housing for displaced residents (non-SV)	% of displaced residents	85	100	60	100
Residents' fear	% residents	25	39	58	65
Symptoms of PTSD	% residents	7	25	18	5
Personal disruption of lifestyle	% residents	50	50	97	70
Number of people who relocate from the community	% residents	3	1	2.8	1.2
Inconvenience to residents	% residents	80	70	100	85
Direct losses	Millions of dollars	1200	480	650	1200

Table 5.8 (continued)

Number of business closures	Count	352	158	146	287
Length of time of business closure	Days	173	88	42	52
Number of permanent business closures	Count	98	50	94	157
Number of residents who cannot find jobs or work again	% residents	12.7	6.5	5.3	3.5
Number of residents who cannot find jobs	% residents	11	11.2	9.8	7
Number of available jobs that cannot find suitable employees	% of jobs	29	87	100	56
Time until available jobs are filled	Days	297	286	285	224
Income losses of SV residents	Millions of dollars	18.522	5.2	2.58	8
Income losses of non-SV residents	Millions of dollars	58.7	36.52	52	78
Residential losses that are not insured	Millions of dollars	79.6	150	139	225
Time to clear debris	Days	14	26	12	24
Miles of highway and road closures	Miles	15	56	59	102
Time for which highways and roads are closed	Days	18	24	28	28
Number of cancelled flights	Count	28	112	78	67
Time to restore normal airport operations	Days	55	74	60	65

Table 5.8 (continued)

Number of waterway port closures	% of ports	25	80	20	50
Time until ports return to full operations	Days	42	48	45	70
Number of residential homes without electricity	Count	750	1237	2300	1800
Time that residential homes do not have electricity	Days	8	9	18	12
Number of commercial buildings without electricity	Count	900	1765	2280	2350
Time that commercial buildings do not have electricity	Days	15	21	21	18
Number of residential homes without gas	Count	1234	2200	3200	3800
Time that residential homes do not have gas	Days	25	33	22	37
Number of commercial buildings without gas	Count	2587	3691	3699	4600
Time that commercial buildings do not have gas	Days	37	54	54	49
Availability of fuel (gasoline)	% of operational gas stations	69	34	55	84
Number of telephone lines/poles damaged	Count	5398	7322	8644	7462
Time to repair telephone lines/poles	Days	150	165	200	140
Number of people who lose internet connectivity	Count	340,000	340,000	140,000	330,000

Table 5.8 (continued)

Time to restore internet connectivity	Days	142	148	35	180
Number of sewage line closures	Count	78	180	280	300
Time to restore sewage lines	Days	11	45	21	37
Number of destroyed homes	Count	280	469	700	580
Time to replace destroyed homes	Days	720	843	750	1200
Number of damaged homes	Count	3267	3600	3200	3200
Time to repair damaged homes	Days	1359	1599	1500	1100
Square miles of habitat destroyed	Sq. miles	547	185	180	200
Time until habitat is restored	Projected years	12	9	6.5	21.5
Number of animals impacted	Count	2944	1578	3800	7000
Pollution in air	Air quality index	135	140	125	128
Pollution in water	Water quality index	58	61	35	48
Pollution in soil	Soil Quality index	48	56	32	82
Agricultural yield loss	Tons	1,200,000	850,000	830,000	530,000
Time to recover agricultural yield loss	Number of harvest cycles	6	3	2	5
Loss of livestock	Count of animals	175,000	145,000	83,000	111,000
Number of people without sufficient food	Count	15,000	25,000	26,500	102,500
Time until food shortage ends	Days	12	17	7	22

Table 5.8 (continued)

Availability of potable water	% of residents with access to potable water	95	96.5	97	92
Ratio of post-disruption capability to pre-disruption capability of medical services	Ratio	0.8	0.95	0.85	0.93
Number of law-enforcement officers available post-disruption	% of pre-disaster availability	45	84	65	96
Number of firefighters available post-disruption	% of pre-disaster availability	93	96	80	99
Number of schools open post-disaster	% of pre-disaster availability	85	75	75	90
Time until all schools are re-opened	Days	14	4	30	21
Number of students who attend schools	% of pre-disaster enrollment	80	75	88	96
Number of employees working in social, safety-net services	% of pre-disaster availability	70	90	100	100

5.4 Evaluation of alternatives

As discussed in Chapter 4, resilience can be calculated using equation (1).

$$R = \sum w_i v_i \tag{1}$$

where R is resilience, w_i is the trade-off weight corresponding to attribute i, and v_i is the value corresponding to attribute i.

The values provided by each alternative, v_i, can be calculated using the value functions elicited in section 5.1. These values are displayed in Table 5.9.

Table 5.9: Values provided by strategies

Attribute	**Strategy 1**	**Strategy 2**	**Strategy 3**	**Strategy 4**
Fatalities (SV residents)	0.8	0.78	0.213	0.787
Injuries (SV residents)	0.633	0.68	0.368	0.48
Displaced residents (SV)	0.76	0.728	0.508	0.48
New housing for displaced residents (SV)	0.85	0.872	0.75	0.93
Fatalities (non-SV residents)	0.85	0.725	0.515	0.87
Injuries (non-SV residents)	0.78	0.846	0.619	0.52
Displaced residents (non-SV)	0.714	0.757	0.714	0.714
New housing for displaced residents (non-SV)	0.85	1	0.6	1
Residents' fear	0.667	0.48	0.227	0.133
Symptoms of PTSD	0.767	0.167	0.4	0.833
Personal disruption of lifestyle	0.5	0.5	0.03	0.3
Number of people who relocate from the community	0.85	0.95	0.86	0.94
Inconvenience to residents	0.2	0.3	0	0.15
Direct losses	0	0.307	0.173	0
Number of business closures Length of time of business closure	0	0.742	0.886	0.724
Number of permanent business closures	0.51	0.75	0.53	0.215
Number of residents who cannot find jobs or work again	0	0.35	0.47	0.65
Number of residents who cannot find jobs	0.45	0.44	0.51	0.65

Table 5.9 (continued)

Number of available jobs that cannot find suitable employees Time until available jobs are filled	0.764	0.318	0.219	0.656
Income losses of SV residents	0	0.653	0.828	0.467
Income losses of non-SV residents	0.413	0.6348	0.48	0.22
Residential losses that are not insured	0.602	0.25	0.305	0
Time to clear debris	0.319	0.054	0.385	0.086
Miles of highway and road closures Time for which highways and roads are closed	0.888	0.44	0.312	0
Number of cancelled flights Time to restore normal airport operations	0.829	0.079	0.48	0.516
Number of waterway port closures Time until ports return to full operations	0.825	0.36	0.85	0.417
Number of residential homes without electricity Time that residential homes do not have electricity	0.8	0.629	0	0.28
Number of commercial buildings without electricity Time that commercial buildings do not have electricity	0.82	0.506	0.361	0.436
Number of residential homes without gas Time that residential homes do not have gas	0.657	0.193	0.218	0
Number of commercial buildings without gas Time that commercial buildings do not have gas	0.681	0.336	0.334	0.249
Availability of fuel (gasoline)	0.69	0.34	0.55	0.84
Number of telephone lines/poles damaged Time to repair telephone lines/poles	0.55	0.329	0.04	0.42
Number of people who lose internet connectivity Time to restore internet connectivity	0.54	0.521	0.953	0.434

Table 5.9 (continued)

Number of sewage line closures Time to restore sewage lines	0.886	0	0.216	0
Number of destroyed homes Time to replace destroyed homes	0.755	0.519	0.361	0.153
Number of damaged homes Time to repair damaged homes	0.513	0.369	0.474	0.614
Square miles of habitat destroyed Time until habitat is restored	0	0.556	0.688	0
Number of animals impacted	0.607	0.79	0.493	0.067
Pollution in air	0.9	0.933	0.833	0.853
Pollution in water	0.508	0.554	0.154	0.354
Pollution in soil	0.35	0.45	0.15	0.775
Agricultural yield loss Time to recover agricultural yield loss	0	0.363	0.585	0.338
Loss of livestock	0.3	0.42	0.668	0.556
Number of people without sufficient food Time until food shortage ends	0.96	0.906	0.959	0.499
Availability of potable water	0.821	0.872	0.889	0.725
Ratio of post-disruption capability to pre-disruption capability of medical services	0.6	0.9	0.7	0.86
Number of law-enforcement officers available post-disruption	0	0.68	0.3	0.92
Number of firefighters available post-disruption	0.86	0.92	0.6	0.98
Number of schools open post-disaster Time until all schools are reopened	0.93	0.967	0.75	0.93
Number of students who attend schools	0.714	0.643	0.829	0.943
Number of employees working in social, safety-net services	0.4	0.8	1	1

These values will be used in equation (1) along with the weights from Table 5.7 to calculate a final resilience value provided by each strategy.

5.5 Results

The resilience provided by the proposed strategies are displayed in Table 5.10.

Table 5.10 Resilience provided by strategies

Alternative	**Resilience**
Strategy 1	0.587
Strategy 2	0.618
Strategy 3	0.548
Strategy 4	0.524

Some strategies perform better than the others in some aspects since each strategy focuses on different aspects of a community. This can be seen in the break down of each strategy as displayed in Figure 5.1 and Table 5.11.

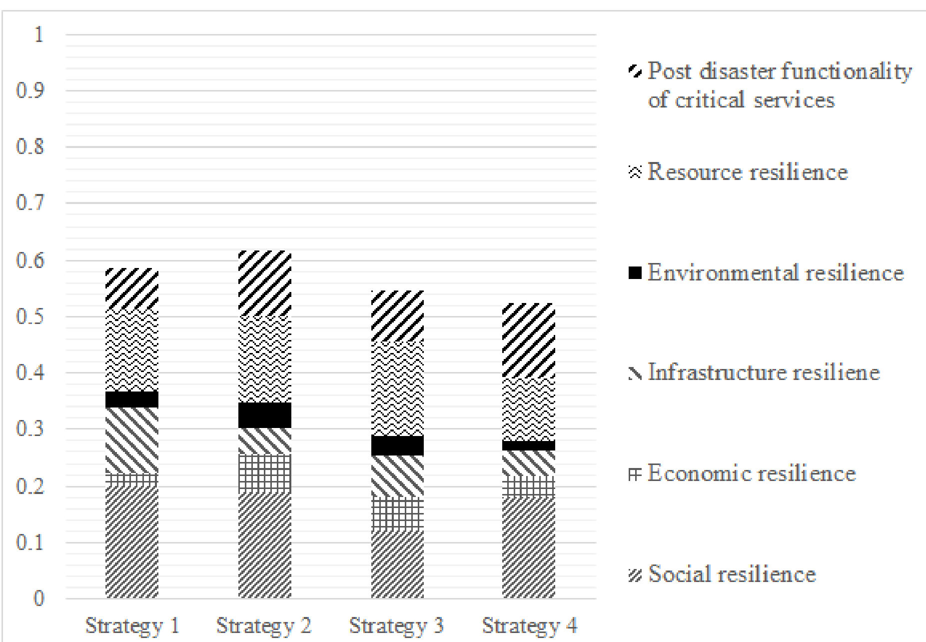

Figure 5.1 Breakdown of strategies

Table 5.11 Breakdown of strategies

Category	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Social resilience	0.199	0.188	0.121	0.181
Economic resilience	0.024	0.068	0.059	0.038
Infrastructure resilience	0.117	0.047	0.073	0.043
Environmental resilience	0.028	0.044	0.034	0.018
Resource resilience	0.145	0.155	0.169	0.114
Post disaster functionality of critical services	0.073	0.115	0.092	0.13
Community resilience	**0.587**	**0.618**	**0.548**	**0.524**

Strategy 2 outperforms the other strategies when it comes to total resilience. This is because the decision makers have placed high importance on social and resource resilience and strategy 2 performs really well in these areas. Strategy 2 also performs well in economic resilience.

CHAPTER 6. CONCLUSION

This thesis aims to apply the principles of decision analysis and VFT to the domain of disaster resilience. It employs an objectives hierarchy to clearly define the objectives of a decision maker. The objectives hierarchy focuses on fundamental objectives of protecting and recovering parts of a community that are necessary for proper functioning: people, economy, infrastructure, environment, resources, and emergency services. The combination of these objectives provide insight into the resilience of a community. Each of these six objectives are decomposed into sub-objectives and eventually result in measurable attributes. Unlike most measures for community resilience currently found in the literature, the attributes proposed in this thesis consist of outcomes from a disruptive event as opposed to inputs or characteristics of a community.

This thesis includes almost scores of attributes that a community leader may want to consider in assessing resilience. The use and importance of these attributes will vary from one community to another. For example, a decision maker from a metropolitan community would place less importance or weight on agricultural resilience. This approach can help a decision maker evaluate and compare strategies for enhancing community resilience. Each strategy for resilience will change the level of multiple attributes in the hierarchy. The knowledge of the decision maker's objectives, value functions, and weights can also help in devising better strategies for increasing a community's resilience.

A limitation of this method is that collecting data for its successful implementation can be very time consuming and poses many obstacles. A lot of data to inform these attributes may not even be available. A consequence of the lack of data is that measuring these attributes will be highly uncertain. Future work on how assess these attributes can incorporate uncertainties, and Monte Carlo simulation can be used to integrate the uncertainties into the VFT approach. Further research can also aggregate the metrics into a final value for resilience. Other decision makers may also want to include more attributes.

Humans have developed technologies to overcome many problems, but natural disasters continue to be a challenge. Since natural events are too big to be prevented, we must focus our efforts towards making our communities more resilient towards disruptions. Many researchers have worked on measuring and improving community resilience, but community leaders still struggle with determining how to implement strategies to enhance their communities' resilience. This thesis constructs measures focused on what decision makers value in order to provide better and more actionable measures for resilience.

REFERENCES

[1] Cutter, S. L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., & Webb, J. (2008). A place-based model for understanding community resilience to natural disasters. Global Environmental Change, 18(4), 598–606.

[2] Cutter, S. L., Burton, C. G., & Emrich, C. T. (2010). Disaster resilience indicators for benchmarking baseline conditions. Journal of Homeland Security and Emergency Management, 7(1).

[3] Cutter, S. L. (2015). The landscape of disaster resilience indicators in the USA. Natural Hazards, 80(2), 741–758.

[4] Frazier, T. G., Thompson, C. M., Dezzani, R. J., & Butsick, D. (2013). Spatial and temporal quantification of resilience at the community scale. Applied Geography, 42, 95–107.

[5] King, D. Natural Hazards (2001) 24: 147.

[6] Noy, I. (2009). The macroeconomic consequences of disasters. Journal of Development Economics, 88(2), 221–231.

[7] Longstaff PH, Armstrong NJ, Perrin K, et al. Building resilient communities: a preliminary framework for assessment. Homeland Security Affairs 2010; 6(3): 1-23.

[8] Renschler, Chris & Frazier, Amy & Arendt, Lucy & Cimellaro, G. & Reinhorn, Andrei & Bruneau, M. (2010). Developing the 'PEOPLES' resilience framework for defining and measuring disaster resilience at the community scale.

[9] Index, C. R. (2014). City resilience framework. The Rockefeller Foundation and ARUP.

[10] Spaans, M., & Waterhout, B. (2017). Building up resilience in cities worldwide – Rotterdam as participant in the 100 Resilient Cities Programme. Cities, 61, 109–116.

[11] Pfefferbaum, R. L., Pfefferbaum, B., Van Horn, R. L., Klomp, R. W., Norris, F. H., & Reissman, D. B. (2013). The communities advancing resilience toolkit (CART): An intervention to build community resilience to disasters. Journal of public health management and practice, 19(3), 250-258.

[12] Bakkensen, L. A., Fox-Lent, C., Read, L. K., & Linkov, I. (2016). Validating Resilience and Vulnerability Indices in the Context of Natural Disasters. Risk Analysis, 37(5), 982–1004.

[13] Peacock, W. G., Brody, S. D., Seitz, W. A., Merrell, W. J., Vedlitz, A., Zahran, S., ... & Stickney, R. (2010). Advancing Resilience of Coastal Localities: Developing, Implementing, and Sustaining the Use of Coastal Resilience Indicators: A Final Report. Hazard Reduction and Recovery Center. Hazard reduction and recovery center.

[14] Foster, K. A. (2012) In search of regional resilience. In N. Pindus, M. Weir, H. Wial, and H. Wolman (eds) Building Regional Resilience: Urban and Regional Policy and its Effects, pp. 24–59. Washington, DC: Brookings Institution Press.

[15] Simon, J., Regnier, E., & Whitney, L. (2014). A Value-Focused Approach to Energy Transformation in the United States Department of Defense. Decision Analysis, 11(2), 117–132.

[16] Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra, 19(4), 733–752.

[17] Hosseini, S., Barker, K., & Ramirez-Marquez, J. E. (2016). A review of definitions and measures of system resilience. Reliability Engineering & System Safety, 145, 47–61.

[18] Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. Decision Support Systems, 50(2), 394–403.

[19] Keeney, Ralph & Raiffa, Howard & Rajala, David. (1979). Decisions with multiple objectives: preferences and value trade-offs. Systems, Man and Cybernetics, IEEE Transactions on. 9. 403 - 403.

[20] Keeney, R. L., & von Winterfeldt, D. (2011). A value model for evaluating homeland security decisions. Risk Analysis, 31(9), 1470–1487.

[21] Wall, K.D., & MacKenzie, C.A. (2015). Multiple objective decision making. In F. Melese, A. Richter, & B. Solomon, eds., Military Cost-Benefit Analysis: Theory and Practice New York: Routledge, 197-236.

[22] Cutter, S. L., Boruff, B. J., & Shirley, W. L. (2003). Social Vulnerability to Environmental Hazards*. Social Science Quarterly, 84(2), 242–261.

[23] Burton, C. G. (2015). A validation of metrics for community resilience to natural hazards and disasters using the recovery from Hurricane Katrina as a case study. Annals of the Association of American Geographers, 105(1), 67-86.

[24] Barnett, J., Lambert, S., & Fry, I. (2008). The hazards of indicators: insights from the environmental vulnerability index. Annals of the Association of American Geographers, 98(1), 102-119.

[25] Fekete, A. (2012). Spatial disaster vulnerability and risk assessments: challenges in their quality and acceptance. Natural hazards, 61(3), 1161-1178.

[26] Fekete, A. (2009). Validation of a social vulnerability index in context to river-floods in Germany. Natural Hazards and Earth System Sciences, 9(2), 393-403.

[27] Hamideh, S., & Rongerude, J. (2018). Social vulnerability and participation in disaster recovery decisions: public housing in Galveston after Hurricane Ike. Natural Hazards.

[28] Sutley, E. J., & Hamideh, S. (2017). An interdisciplinary system dynamics model for post-disaster housing recovery. Sustainable and Resilient Infrastructure, 3(3), 109–127.

[29] Hamideh, S. (2015). Women confronting natural disasters: from vulnerability to resilience (2015). Community and Regional Planning Publications. 32.

[30] Jonkman, S. N., Vrijling, J. K., & Vrouwenvelder, A. C. W. M. (2008). Methods for the estimation of loss of life due to floods: a literature review and a proposal for a new method. Natural Hazards, 46(3), 353–389.

[31] Keeney, R. L., & Von Winterfeldt, D. (2011). A value model for evaluating homeland security decisions. Risk Analysis: An International Journal, 31(9), 1470-1487.

[32] Okuyama, Y., & Santos, J. R. (2014). Disaster impact and input–output analysis. Economic Systems Research, 26(1), 1–12.

[33] Hallegatte, S. (2013). Modeling the Role of Inventories and Heterogeneity in the Assessment of the Economic Costs of Natural Disasters. Risk Analysis, 34(1), 152–167.

[34] Davis, H. C., & Salkin, E. L. (1984). Alternative approaches to the estimation of economic impacts resulting from supply constraints. The Annals of Regional Science, 18(2), 25–34.

[35] Wei, H., Dong, M., & Sun, S. (2009). Inoperability input-output modeling (IIM) of disruptions to supply chain networks. Systems Engineering.

[36] Rose, A. Z., Oladosu, G., Lee, B., & Asay, G. B. (2009). The economic impacts of the September 11 terrorist attacks: a computable general equilibrium analysis. Peace Economics, Peace Science and Public Policy, 15(2).

[37] Rose, A., Wei, D., & Wein, A. (2011). Economic impacts of the shakeout scenario. Earthquake Spectra, 27(2), 539–557.

[38] Ferreira, S., & Karali, B. (2015). Do earthquakes shake stock markets? PLOS ONE, 10(7), e0133319.

[39] Webb, G. R., Tierney, K. J., & Dahlhamer, J. M. (2002). Predicting long-term business recovery from disaster: a comparison of the Loma Prieta earthquake and Hurricane Andrew. Environmental Hazards, 4(2), 45–58.

[40] Porter, J.M. (2011). Regional Economic Resilience and the Deepwater Horizon Oil Spill: The Case of New Orleans' Tourism and Fishing Clusters.

[41] Martinelli, D., Cimellaro, G. P., Terzic, V., & Mahin, S. (2014). Analysis of economic resiliency of communities affected by natural disasters: the bay area case study. Procedia Economics and Finance, 18, 959–968.

[42] Adam Rose (2007) Economic resilience to natural and man-made disasters: Multidisciplinary origins and contextual dimensions, Environmental Hazards, 7:4, 383-398

[43] Xiao, Y. (2011). Local economic impacts of natural disasters*. Journal of Regional Science, 51(4), 804–820.

[44] Zobel, C. W. (2011). Representing perceived tradeoffs in defining disaster resilience. Decision Support Systems, 50(2), 394–403.

[45] Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., ... von Winterfeldt, D. (2003). A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities. Earthquake Spectra, 19(4), 733–752.

[46] Alderson, D., Brown, G., Carlyle, W., & Cox, L. (2013). Sometimes There Is No "Most-Vital" Arc: Assessing and Improving the Operational Resilience of Systems. Military Operations Research, 18(1), 21-37.

[47] Fisher, R. E., Bassett, G. W., Buehring, W. A., Collins, M. J., Dickinson, D. C., Eaton, L. K., ... & Millier, D. J. (2010). Constructing a resilience index for the enhanced critical infrastructure protection program (No. ANL/DIS-10-9). Argonne National Lab.(ANL), Argonne, IL (United States). Decision and Information Sciences.

[48] Setola, R., De Porcellinis, S., & Sforna, M. (2009). Critical infrastructure dependency assessment using the input–output inoperability model. International Journal of Critical Infrastructure Protection, 2(4), 170–178.

[49] Reed, D. A., Kapur, K. C., & Christie, R. D. (2009). Methodology for Assessing the Resilience of Networked Infrastructure. IEEE Systems Journal, 3(2), 174–180.

[50] McDaniels, T., Chang, S., Cole, D., Mikawoz, J., & Longstaff, H. (2008). Fostering resilience to extreme events within infrastructure systems: Characterizing decision contexts for mitigation and adaptation. Global Environmental Change, 18(2), 310–318.

[51] Faturechi, R., & Miller-Hooks, E. (2014). Travel time resilience of roadway networks under disaster. Transportation Research Part B: Methodological, 70, 47–64.

[52] Jin, J. G., Tang, L. C., Sun, L., & Lee, D.-H. (2014). Enhancing metro network resilience via localized integration with bus services. Transportation Research Part E: Logistics and Transportation Review, 63, 17–30.

[53] Miller-Hooks, E., Zhang, X., & Faturechi, R. (2012). Measuring and maximizing resilience of freight transportation networks. Computers & Operations Research, 39(7), 1633–1643.

[54] Faturechi, R., Levenberg, E., & Miller-Hooks, E. (2014). Evaluating and optimizing resilience of airport pavement networks. Computers & Operations Research, 43, 335–348.

[55] MacKenzie, C. A., Barker, K., & Grant, F. H. (2012). Evaluating the Consequences of an Inland Waterway Port Closure With a Dynamic Multiregional Interdependence Model. IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 42(2), 359–370.

[56] Wilson, M. C. (2007). The impact of transportation disruptions on supply chain performance. Transportation Research Part E: Logistics and Transportation Review, 43(4), 295–320.

[57] Gordon, P., Richardson, H., Davis, B. (1998). Transport-related impacts of the northridge earthquake. Journal of Transportation and Statistics 1, 21–36

[58] Chang, S. E., & Nojima, N. (2001). Measuring post-disaster transportation system performance: the 1995 Kobe earthquake in comparative perspective. Transportation Research Part A: Policy and Practice, 35(6), 475–494.

[59] MacKenzie, C. A., & Barker, K. (2013). Empirical data and regression analysis for estimation of infrastructure resilience with application to electric power outages. Journal of Infrastructure Systems, 19(1), 25–35.

[60] Liu, H., Davidson, R. A., & Apanasovich, T. V. (2008). Spatial generalized linear mixed models of electric power outages due to hurricanes and ice storms. Reliability Engineering & System Safety, 93(6), 897–912.

[61] Guikema, S. D., Quiring, S. M., & Han, S.-R. (2010). Prestorm estimation of hurricane damage to electric power distribution systems. Risk Analysis, 30(12), 1744–1752.

[62] Rafee, N., Karbassi, A. R., Safari, E., Mehrdadi, M. (2008). Strategic management of municipal debris aftermath of an earthquake. Int. J. Environ. Res. 2, 205-214.

[63] Swan, R. C. (2000). Debris Management Planning for the 21st Century. Natural Hazards Review, 1(4), 222–225.

[64] Luther, L.. (2009). Disaster debris removal after Hurricane Katrina: Status and associated issues.

[65] Yodmani, Suvit & Hollister, David. (2001). Disasters and Communication Technology: Perspectives from Asia.

[66] Kwasinski, A. (2011). Effects of notable natural disasters from 2005 to 2011 on telecommunications infrastructure: Lessons from on-site damage assessments. 2011 IEEE 33rd International Telecommunications Energy Conference (INTELEC).

[67] Houston, J. B., Spialek, M. L., Cox, J., Greenwood, M. M., & First, J. (2014). The Centrality of Communication and Media in Fostering Community Resilience. American Behavioral Scientist, 59(2), 270–283.

[68] Pfefferbaum, Rose & Neas, Barbara & Pfefferbaum, Betty & Norris, Fran & Horn, Richard. (2013). The Communities Advancing Resilience Toolkit (CART): Development of a survey instrument to assess community resilience. International journal of emergency mental health. 15. 15-29.

[69] Norris, F. H., Stevens, S. P., Pfefferbaum, B., Wyche, K. F., & Pfefferbaum, R. L. (2007). Community Resilience as a Metaphor, Theory, Set of Capacities, and Strategy for Disaster Readiness. American Journal of Community Psychology, 41(1–2), 127–150.

[70] Alam, P., & Ahmade, K. (2013). Impact of solid waste on health and the environment. International Journal of Sustainable Development and Green Economics (IJSDGE), 2(1), 165-168.

[71] Lechat, M. F. (1990). The epidemiology of health effects of disasters. Epidemiologic reviews, 12(1), 192-198.

[72] Allen, R. B., Bellingham, P. J., & Wiser, S. K. (1999). Immediate damage by an earthquake to a temperate montane forest. Ecology, 80(2), 708-714.

[73] Bahuguna, A., Nayak, S., & Roy, D. (2008). Impact of the tsunami and earthquake of 26th December 2004 on the vital coastal ecosystems of the Andaman and Nicobar Islands assessed using RESOURCESAT AWiFS data. International Journal of Applied Earth Observation and Geoinformation, 10(2), 229-237.

[74] Newell, R. E. (1970). Stratospheric temperature change from the Mt. Agung volcanic eruption of 1963. J. Atmos. Sci.;(United States), 27(6).

[75] Sigurdsson, H. (1982). Volcanic pollution and climate: the 1783 Laki eruption. Eos, Transactions American Geophysical Union, 63(32), 601-602.

[76] Qiao, J., Jeong, D., Lawley, M., Richard, J. P. P., Abraham, D. M., & Yih, Y. (2007). Allocating security resources to a water supply network. IIE Transactions, 39(1), 95-109.

[77] Luna, R., Balakrishnan, N., & Dagli, C. H. (2011). Postearthquake recovery of a water distribution system: discrete event simulation using colored petri nets. Journal of Infrastructure Systems, 17(1), 25-34.

[78] Walchuk, Z., & Barker, K. (2013). Analyzing interdependent impacts of resource sustainability. Environment Systems and Decisions, 33(3), 391-403.

[79] Israel, D. C., & Briones, R. M. (2012). Impacts of natural disasters on agriculture, food security, and natural resources and environment in the Philippines (No. 2012-36). PIDS discussion paper series

[80] Aubuchon, C. P., & Morley, K. M. (2013). The economic value of water: providing confidence and context to FEMA's methodology. Journal of Homeland Security and Emergency Management, 10(1), 245-265.

[81] De Haen, H., & Hemrich, G. (2007). The economics of natural disasters: implications and challenges for food security. Agricultural economics, 37, 31-45.

[82] Schneider, S. M., Gallery, M. E., Schafermeyer, R., & Zwemer, F. L. (2003). Emergency department crowding: a point in time. Annals of emergency medicine, 42(2), 167-172.

[83] Saliba, D., Buchanan, J., & Kington, R. S. (2004). Function and response of nursing facilities during community disaster. American Journal of Public Health, 94(8), 1436-1441.

[84] Dela Cruz, D. A. (2017). The role of schools and their capabilities to ensure safe sheltering during a storm. Naval Postgraduate School Monterey United States.

[85] Convery, I., Carroll, B., & Balogh, R. (2015). Flooding and schools: experiences in Hull in 2007. Disasters, 39(1), 146-165.

[86] Mitchell, J. T., & Dyregrov, A. (1993). Traumatic stress in disaster workers and emergency personnel. In International handbook of traumatic stress syndromes (pp. 905-914). Springer, Boston, MA.

[87] Masterson, L., Steffen, C., Brin, M., Kordick, M. F., & Christos, S. (2009). Willingness to respond: of emergency department personnel and their predicted participation in mass casualty terrorist events. The Journal of emergency medicine, 36(1), 43-49.

[88] Pelham, L., Clay, E., & Braunholz, T. (2011). Natural disasters: what is the role for social safety nets?. World Bank.

[89] Briguglio, L., Cordina, G., Farrugia, N., & Vella, S. (2009). Economic vulnerability and resilience: concepts and measurements. Oxford development studies, 37(3), 229-247.

[90] Keeney, R. L. (1996). Value-Focused Thinking: A Path to Creative Decisionmaking. Cambridge, MA: Harvard University Press.

[91] Keeney, R. L., & McDaniels, T. L. (1992). Value-focused thinking about strategic decisions at BC Hydro. Interfaces, 22(6), 94-109.

[92] Merrick, J. R., & Garcia, M. W. (2004). Using value-focused thinking to improve watersheds. Journal of the American Planning Association, 70(3), 313-327.

[93] Keisler, J., Turcotte, D. A., Drew, R., & Johnson, M. P. (2014). Value-focused thinking for community-based organizations: objectives and acceptance in local development. EURO Journal on Decision Processes, 2(3-4), 221-256.

[94] Kaji, A. H., & Lewis, R. J. (2006). Hospital disaster preparedness in Los Angeles county. Academic emergency medicine, 13(11), 1198-1203.

[95] Chapman, K., & Arbon, P. (2008). Are nurses ready?: disaster preparedness in the acute setting. Australasian Emergency Nursing Journal, 11(3), 135-144.

[96] Bonanno, G. A., Galea, S., Bucciarelli, A., & Vlahov, D. (2006). Psychological resilience after disaster: New York City in the aftermath of the September 11th terrorist attack. Psychological Science, 17(3), 181-186

[97] MacKenzie, C. A., & Zobel, C. W. (2016). Allocating resources to enhance resilience, with application to superstorm sandy and an electric utility. Risk Analysis, 36(4), 847-862.

[98] Ayyub, B. M. (2015). Practical resilience metrics for planning, design, and decision making. ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering, 1(3), 04015008.

[99] Henry, D., & Ramirez-Marquez, J. E. (2012). Generic metrics and quantitative approaches for system resilience as a function of time. Reliability Engineering & System Safety, 99, 114-122.

[100] Zobel, C. W., & Khansa, L. (2012). Quantifying cyberinfrastructure resilience against multi-event attacks. Decision Sciences, 43(4), 687-710.