A Societally-Optimized Resource Distribution (SORD) Framework for Community Flood Recovery

By
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Abstract

Natural hazards and disasters affect different populations within communities unevenly. However, natural hazards do not have the ability to discriminate between the population of the community; rather, it is the pre-existing socioeconomic conditions and the responses made to the hazards that cause disasters to be inequitable. Despite historical studies showing the disproportionate damages occurring to socially disadvantaged inhabitants, there has been limited studies demonstrating a systematic pursuit of equitable outcomes to natural hazards, particularly related to federal policy. Increasing rates and intensities of natural hazards, coupled with rising urbanization and more expensive infrastructure, underlines the criticality of addressing this shortcoming.

A Societally-Optimized Resource Distribution (SORD) framework has been proposed to tackle the issue of socially unjust disasters. The novel framework centers the design of disaster resource distribution around the principles of social justice; equality and equity. Using computational optimization, it is intended that the resource distribution strategies developed through the SORD framework are first and foremost designed for the goal of fairness in the outcomes of a natural hazard. The SORD framework uses six main steps to achieve this goal: 1) hazard identification, 2) choosing societal damage indicators, 3) developing a community portfolio, 4) choosing resource types and amounts, 5) performing optimization, and 6) evaluation and decision-making.

In order to demonstrate the SORD framework, an illustrative case study is provided using the 2016 flooding in Lumberton, NC. A community portfolio was developed for Lumberton using post-disaster household and business surveys completed as part of a longitudinal disaster recovery study by the NIST Center for Risk-Based Community Resilience Planning. Through the SORD

framework, equality- and equity-based resource distribution strategies were developed and evaluated for the case of riverine flooding caused by the heavy rains of 2016 Hurricane Matthew. Structural retrofits were used as the resources for disaster mitigation, and household dislocation duration and business downtime duration were used as the metrics to gauge societal fairness. Using these metrics, equity was described using an average difference in days of dislocation and downtime amongst households and businesses, respectively, where a lower average difference is more equitable.

The evaluations of the retrofit distributions obtained for Lumberton demonstrated that equity-based strategies were desirable compared to those based on equality. Equitable strategies were observed to have greater cost-efficiency not only in increasing equity per $1 million spent, but also in decreasing total days of dislocation and downtime. The high cost-efficiency was achieved with only minimal increases in total days of dislocation and downtime, compared to the equality-based distribution strategies. The results of the case study demonstrate great promise in the current version of the SORD framework. Future work in developing the SORD framework includes providing direction on considering long-term hazards, such as droughts, and non-structural types of resources for disaster mitigation and recovery.

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1. Introduction

Consider the trends of disasters in the United States; the prevalence of natural hazards in every region of the country, coupled with numerous high-density populated areas and expensive infrastructure, makes extensive damages and societal disruption inevitable. However, the impacts of severe hazard events are often overgeneralized. Indeed, the Billion-Dollar Weather and Climate Disasters report from the National Centers for Environmental Information illustrates this emphatically, reporting fourteen weather-related natural disaster events causing over one billion dollars of damage each in 2019 alone (NCEI 2020). However, their report depends on just two statistics most frequently used for characterizing the consequences of a disaster event: the total direct monetary cost of damages and the number of fatalities.

Because of the focus placed on direct damages, what become overlooked are the indirect losses resulting from these events. Indirect losses are those which are caused as a result of direct damages. In other words, indirect losses can be described as second-order effects. Some of the most recognizable indirect losses may be found in the business world: losses of sales and wages, supply chain disruptions, opportunity losses, et cetera. Obviously, indirect losses are not limited to businesses. There are also severe second-order societal implications from disaster events which contribute to the overall societal damages that are felt within and across affected communities. Societal damages are those which negatively affect the ability of humans to live in a society at either their normal or desirable level of capability and opportunity. Societal damages differ from other damages, such as to the built environment or infrastructure, in that they are defined in the context of humans. Examples of societal damages include physical or mental injury, loss of income and personal property, loss of accessibility to resources and services, and loss of short-term and long-term opportunities.

The critical issue is that societal damage can be difficult to quantify, and even to identify in the first place, meaning they are easily overshadowed by direct losses. Effectively, the overall losses of a disaster event can be severely underestimated. It is crucial that this trend does not shape how disaster management is practiced. Therefore, the initial purpose of this research was to realign the perspective of measuring damages when preparing for hazard events. It was desired to produce a framework that encouraged focusing on society when preparing for hazards, and even possibly establish limiting societal damages as the main objective of these management practices.

Preparation can take many forms, such as through engineered mitigation solutions, deliberate urban planning decisions, and preemptive policy-making. All of these forms of preparation are also dependent on knowing how to effectively distribute the resources needed to perform the preparations. There are many types of resources that can be distributed, such as money, material, information and human labor, and choices have to be made in how they are distributed. Some decisions are made at the federal level, and others at the local level. In both cases, effectively managing the distribution of resources is difficult because resource distribution can easily appear to be unfair, let alone ineffective, depending on whose perspective is taken.

Unfortunately, societal damage in itself has also been found to be fundamentally unfair. Natural hazards have no capability to discriminate against certain portions of a population. However, society has designed cities and neighborhoods, as well as access to opportunities and resources, in such a way that the resulting damages and other consequences most often do so. It has been recognized for a considerable amount of time now how the vulnerability to a hazard event become ‘magnified’ for those already socially disadvantaged without the threat of additional hazards (Fothergill and Peek 2004). This magnification occurs because the disadvantaged population have some combination of worse access to services and resources (such as due to

language barriers or racial bias), smaller amounts of savings to recover with, and less robust shelters which will be more damaged than those of their wealthier neighbors; all of these issues mean that the disadvantaged population *begin* at a relatively weaker state, and following damages (societal and otherwise) therefore become higher. This phenomenon has been referred to as the 'lens of vulnerability'. French et al. (2008) showed that even in the cases where resources were distributed evenly to both advantaged and disadvantaged groups, the latter were often disproportionally impacted by the same natural hazard because of the other difficulties that they already face outside of hazards.

Accordingly, the purpose of this dissertation evolved to also promote societal fairness as an objective in disaster resource management. Societal fairness, in this case, is proposed as the idea that the asymmetry in the people's experiences due to a disaster event can be minimized. As done for many similar types of maximization/minimization problems in engineering, the main method used to achieve this objective was through computational optimization.

1.1 Flood Disasters in the United States

Flooding is a particularly dangerous natural hazard worldwide, including in the United States. The Billion-Dollar Weather and Climate Related Disasters report by NCEI lists flooding as the primary cause of approximately 12% of all billion-dollar events since 1980, among seven types of disasters (NCEI 2020). Note that this percentage only includes inland, non-hurricane flooding. Tropical storms (hurricanes), severe storms, winter storms, and freeze can all be accompanied by secondary flooding as well; counting all the billion-dollar events of the listed types increases the percentage of potential-flood events to a maximum of 83% of events since 1980.

As with the other types of disasters, high damage flooding events are increasing in potential for damage with the increased urbanization and infrastructure development across the United States. This has been compounded by continued development in flood-prone regions (such as on floodplains and in coastal areas), oftentimes driven by the desire for affordable housing that gets positioned on land that is otherwise undesirable. The City of Houston, TX, is one of many examples where drastic urban sprawl brought low-density development, and, crucially, affordable homes near reservoirs and the coast. The relatively low cost of the homes brought in many households, including low-income families (many of whom were displaced from Hurricane Katrina) who would end up living by the reservoirs due to the affordability. Unfortunately, flooding was inevitable in Houston, given the at least 40 severe events in the past century, and 2017 Hurricane Harvey was no different. Harvey, much like Tropical Storm Allison in 2001, Hurricane Ike in 2008, and Tropical Storm Imelda in 2019, brought heavy rains over the vast concrete-paved metropolitan area, causing immense damages and disruption, which could have largely been avoided through more appropriate land-use planning.

Since 1968, the Federal Emergency Management Agency (FEMA) has operated the National Flood Insurance Program (NFIP) to disseminate the risk of flood losses to multiple parties, as well as to reduce flood damage potential by effectively dissuading the development of floodplains (in some regions of the United States, the purchasing of flood insurance is mandatory). However, even this program appears to be becoming overwhelmed by recent trends in flood disasters, like the $11 billion of damages from Hurricane Harvey insured by the NFIP alone. An article published by the Wall Street Journal purports that the NFIP has accumulated severe debts (approximately $25 billion at the time of article publishing) due to insurance payouts for recent massive disaster events, such as 2012 Hurricane Sandy (Witkowski and Scism 2017) and Harvey.

As the costs of flood disasters increase, the same may be the case for societal damages. This can be especially true for those with greater social vulnerability, who have to contend with the increasing costs with limited income, often no insurance, and a generally overladen support system. However, the latter, which relies upon a strong management of disbursing resources, has the potential to be made more effective as argued prior. Therefore, this dissertation placed focus on disaster resource management, particularly in the form of mitigation resources. The latest interim report issued by the Multihazard Mitigation Council of the National Institute of Building Sciences, as part of their ongoing Natural Hazard Mitigation Saves Study, expresses that investments into hurricane surge and riverine flood mitigation can result in national benefits of between *five to eight* times the original investment amount (Multihazard Mitigation Council 2018). This finding provides a clear argument for enhancing, as much as possible, the quality of the disaster resource management that is being conducted.

1.2 Definitions

This dissertation is situated in a multidisciplinary research space. Some of the terms and concepts used in this field of research are shared between civil engineering, urban planning, economics and sociology with differing contexts, which means the meaning of critical terms used herein may be ambiguous. Therefore, several concepts or terms are introduced and defined in this section. Resilience, specifically community disaster resilience, and societal fairness are discussed to appropriately position them within this dissertation work.

1.2.1 Resilience

Resilience is a quality which describes the ability of a system or object to recover from a shock or disturbance. Resilience is a concept already well-explored in structural engineering,

especially for buildings or structural systems, though the concept can be expanded well beyond the footprint of the structure. For example, Bruneau et al. (2003) defines resilience in the context of seismic resilience, in which the ability is considered to be a function of three capacities: 1) reducing the effects of the shock, 2) reducing the effects due to system failure from the shock, and 3) reducing the time to recover to pre-shock levels. Bruneau et al. further describes the properties inherent to the system which informs these capacities using the 'four Rs': robustness, redundancy, resourcefulness and rapidity. The properties themselves may also exist in the four dimensions of technical, organizational, social and economic. In other words, the definition provided suggests that in (seismic) resilience, one must consider the non-physical factors or resources that exist in the system to completely categorize a system's resilience. This is certainly true in the case of analyzing communities as systems.

1.2.1.1 Community Disaster Resilience

An elemental definition of community disaster resilience is the implementation of resilience concepts to a community, typically for the goals of reduced damages and rapid recovery. There is no common consensus on the complete definition of this concept. There are strong commonalities between the definitions in the literature, however, as observed in a review conducted by Patel et al. (2017). Amongst eighty papers, Patel et al. identified nine 'core elements' that frequently compose general community resilience. This observation highlighted that the non-physical elements of community resilience, such as communication, organization and perceptions, often outnumbered the physical attributes of a community.

Indeed, a community consists of many nested systems, including the human systems (such as individuals, households, businesses, neighborhoods, governments and other organizations), the built environment (the buildings and other structures, the utility and transportation infrastructures,

and designed landscaping), and the natural geology and climate surrounding both. Because of the existence of all these systems, and the complicated interactions between said systems, community disaster resilience can be much more difficult to realize compared to other applications of resilience.

Within the context of this dissertation, community disaster resilience is referred to as the ability of said community's population to recover to some defined level of operability or prosperity after the occurrence of a shock or disturbance. The level of operability or prosperity of the population was in turn quantified through the metrics of societal damage.

It is important to note that critical to the concept of community disaster resilience is *building back better*, which implies that the recovery path taken can situate a system very differently than it was before. The ideal recovery path does not emerge naturally, without prompting. Similarly, disaster resilience should not be expected to develop spontaneously. Community disaster resilience must be designed and implemented deliberately to be meaningful.

The desired goals of the designed community disaster resilience has been taken as the following: 1) an increase in the initial ability of the community to withstand the shock, and 2) an efficient and effective recovery process suited for the target population. The latter may be regarded as a function of available resources, redundancy in recovery systems and the rate at which these systems operate. This dissertation focused on the availability of resources by examining how a pool of resources could be distributed amongst the population.

Societal damage is another term used herein that has limited connotation in traditional structural engineering. Despite the role of structural engineers in society, 'damage' for engineered products typically takes a physical form. It is only afterwards that this damage is translated into a

societal form, such as through monetary cost, functionality loss or downtime. These are some examples of societal damage; negative consequences which are imposed on people, organizations or other similar forms of society as a result of an event. Due to the nature of humans and organizations, the number of possible forms of societal damage are many magnitudes greater than physical damages.

1.2.1.2 Buildings in Community Disaster Resilience

For households and some businesses, the vast majority of the value of their physical property will be tied to the buildings in which they reside and the associated contents. Buildings also provide intrinsic value by enabling occupants to perform much of their daily routine, as well as by providing shelter during regular use and potentially during hazard events. That is to say, the performance and functionality of an occupant's building will have very strong correlations to their personal well-being. Damages occurring to the building would then lead to second-order societal damages to the occupants, such as household dislocation and business downtime. These individual-level societal damages will likely transfer to the general community as well due to the high interconnectivity explained prior.

Fortunately, buildings are the most accessible targets for disaster resource application from the perspective of structural engineering, and are well-aligned with existing federal- and state-level mitigation and recovery programs. Types of mitigation strategies available for most hazards, and exactly how they affect the building, are generally understood. The issue is not designing structures to withstand hazard loads, but rather to do it in an affordable, equitable, and efficient manner. For example, Mieler et al. describe a framework for setting performance objectives for probabilistic community-resilience goals (Mieler et al. 2015), a practice that is *not* commonplace with typical construction projects.

Two main options exist for the flood disaster mitigation of buildings in an established city. Given that the majority of the building inventory are existing structures, rather those under construction, retrofitting is most applicable here. The other option is the relocation of existing buildings out of high-risk areas. Conventional flood mitigation techniques are explored further in Chapter 2.

1.2.1.3 Sustainability and Resilience

Sustainability is brought into light within this dissertation due to it being the driving force for many research activities. For several decades now, formally in the United States since the passing of the National Environmental Policy Act (NEPA) of 1969 and with international cooperation through the United Nations Conference on Environment and Development in 1992, sustainability has been one of the main overarching goals for innumerable actions. The modern surge for sustainable development and practices could be credited to the Millennium Summit of the United Nations, during which global sustainability was established as a Millennium Development Goal (United Nations 2000).

The concept of sustainability was originally associated with environmental preservation, though its domain has expanded considerably over time. Recall the three conventional facets of sustainability: economical, environmental and societal. These constitute the 'triple bottom line', a term often attributed to John Elkington. Elkington, a management consultant at the time, originally used the term to describe the worth or performance of businesses; to describe how a business should be measured not only by their profitability, but also their contributions to both the general population and to the planet on which the business thrives. Over the years, 'profit, people, planet' evolved beyond the business world to the three pillars of 'economy, environment, and equity (society)'. It is now one of the most acknowledged working definitions for a sustainable system or

practice, including locally in the United States through the NEPA and by the Environmental Protection Agency (USEPA 2013).

The concepts of resiliency and sustainability often coincide and intersect, especially when used in the context of hazards and disaster research. Resilient buildings and structures are perceived as being especially valuable; after all, structures that need limited repairs and no replacing after severe natural hazards or other shocks conserve money, resources, and time. In the same way, community resilience can imply community sustainability. Suppose measures are put into place such that the impact of an event is minimized, and plenty of resources are stockpiled to overcome the results of the event. Ideally, the following restoration to pre-event normal will incur fewer costs, time, and natural resources. The local economy returns to its original equilibrium (or better), and the community will be able to return to their (new) everyday routines. Arguably, the volume of resources (monetary and otherwise) that is necessary upfront to produce resilient structures and communities may upset the balance of sustainability, most often if the design-level shock never appears to occur.

By the nature of its process, resource distribution's role within community disaster resilience may perhaps be most associated to the balance of economy and society, and less so towards the environment. These two tenets are often prioritized in emergency situations over the latter. However, the overall sustainability of a *community* may ultimately be enhanced through the study of resilience, including through enhanced resource distribution methodologies.

1.2.2 Societal Fairness

The aforementioned sustainable balance of economy and society may be achieved in disaster resource management by adopting the principles of societal fairness. The two terms

‘equality’ and ‘equity’ have been used extensively when describing the societal fairness of a system or process, though not very often in structural engineering, and not often enough in disaster resource management practice. In essence, the two concepts have a similar aim in placing people at an equivalent position. The difference between equality and equity can be briefly defined as *when* the fairness is achieved; typically at the beginning of some process for equality, and at the end for equity.

Note that these two goals are not mutually exclusive. John Rawls, a philosopher, expresses in his book *A Theory of Justice* the principle of ‘justice as fairness’, a political theory of distributive justice based upon the tradition of social contracts (Rawls 1971). Rawls defines two principles of justice as the ‘greatest equal liberty principle’ and the ‘equal opportunity principle’; the latter itself consists of two parts (‘the Difference Principle’ and the aforementioned ‘Equal Opportunity Principle’) that may be succinctly described as equity and equality. Both, as a part of the encompassing principle of justice as fairness, are suggested to form the basis of the modern progressive welfare state (Young 2013).

It was hypothesized that the introduction of these two principles into the resource distribution problem can lead towards communities which are at least sustainable both societally and economically, and preferably environmentally as well. However, planners have identified that the concept of equity, in particular within communities, has been frequently marred by inconsistent or incomplete definitions thereof, leaving such resources to be taken advantage of by hegemonic ideals and creating greater disparities between the social groups of a community (Schrock et al. 2015). Additionally, the lens of vulnerability previously discussed is another hurdle in achieving ‘fairness in societal fairness’. Therefore, care was placed such that first the concepts of social fairness used in this dissertation were unambiguously defined and differentiated, such as through

the use of mathematical representations, and second that more than a single form of societal fairness was examined.

1.3 Problem Statement

The purpose of this dissertation is to expand the body of knowledge of community disaster resilience and to enhance future disaster planning by highlighting the practicality of using societal damage metrics when designing resource management and distribution strategies. The goal was not to replace existing resource management practices, but to complement them with additional potential design objectives that may prove more efficient and sustainable.

Disasters exacerbate pre-existing inequities; they hit the most socially vulnerable community members harder and more often, and leave these people with the most difficult and longest recovery trajectories due to a lack of resources and neglectful post-disaster policies. Thus, the overarching research question for this dissertation is 'How can disaster resources be distributed in a community for equitable recovery?' The research hypothesis is that through the development and incorporation of societal damage metrics, such as the average differences in dislocation time for households and downtime for businesses, into a novel resource distribution design framework, post-disaster outcomes can be equitably experienced via optimized distributions of pre- or post-disaster resources.

To test the research hypothesis, a framework entitled 'Societally-Optimized Resource Distribution (SORD)' was developed. The framework describes, in-depth, six steps that should be undertaken in order to sufficiently incorporate societal damage into the design of resource distribution plans. The framework is predominately positioned in the realm of flood hazards, though it is applicable for most other types of hazard events. The framework was exemplified

using a case study positioned in a real historical disaster scenario, the flooding in Lumberton, NC, due to 2016 Hurricane Matthew.

1.3.1 Framework

The major outcomes of this dissertation research is presented in the form of the SORD framework. The development of this framework entailed establishing new philosophies for resource distribution with an overarching idea of using societal damage across the community as the defining measure of effectiveness.

The research and development performed as part of this project was a multi-disciplinary endeavor. Community disaster resilience, already at the intersect of emergency and disaster management, sociology and psychology, social justice, public policy, urban planning, and a plethora of other fields of study, was further augmented with structural and systems engineering philosophies and practices.

Societal damage was quantified through the lens of societal fairness, namely with the goals of optimizing resource distribution for equality or equity amongst the recipients. Note that though it was previously argued that these two forms of societal fairness are not mutually exclusive, they are considered to be separate goals in the context of this framework. This does not mean that one must choose one or the other, but rather that they should first be examined individually, then merged together if necessary.

The framework is intended to provide adequate guidance in identifying and completing numerous procedures, including setting objectives, data collection, interpretation, analysis, design, and evaluation. These procedures are already frequently used in many engineering-adjacent circles, though not necessarily in the same order, in the same fashion, or for the same purpose.

Therefore, it is expected that the framework will be comfortably accessible by most people involved in community disaster resilience, scholars and practitioners alike.

1.3.2 Case Study

The methodologies resulting from this process were implemented and evaluated in a case study of a flood scenario occurring in Lumberton, NC. In 2016, the southern portion of Lumberton was flooded due to heavy rainfall accompanying Hurricane Matthew. Much of the same portions of Lumberton was flooded again in 2018 following Hurricane Florence. The case study is positioned between the two disaster events. Collected data regarding household and business demographics were paired with observed physical and societal damages from the Hurricane Matthew event to develop a resource management plan for a Matthew-level flood event.

Lumberton was identified as a suitable testbed for this framework due to the characteristics of the community. This was not decided solely by the city's proximity to the Lumber River and the resulting heavy flooding. The population of the city is quite diverse in terms of personal identity, wealth, and household structure. The built environment is also suitably diverse, by building type, purpose and potential for flood mitigation. As examined in this dissertation, and beyond by Sutley et al. (n.d.), these types of diversity result in varying levels of social vulnerability across the community. This variance in social vulnerability is why societal fairness can be applied as an objective for resource distribution.

It should be emphasized that the specific results of this case study are not expected to be generally applicable for all flood hazard scenarios. The characteristics of the city of Lumberton are unique to itself, as are the conditions surrounding Hurricane Matthew (and Hurricane Florence) to cause the flooding. However, what the case study does offer is a procedure which may be

repeated or adapted to apply the principles of equality and equity to disaster resource distribution methods in other community and hazard scenarios. Equality- and equity-based metrics were developed and incorporated into the framework to further enhance broad applicability.

1.3.3 Intended Audience

The findings of this research are intended to exemplify the deliberate incorporation of societal fairness into resource management. The intended audience of the framework developed through this research are policy- and decision-makers in disaster management. The findings from the case study may also be generalizable spatially by these audiences to address local, regional (county or state-level) or even national resource distribution for disaster mitigation. This dissertation and eventual journal papers will be the primary method of communicating this research, though technical presentations made directly to these policy-makers will likely be more influential. In addition, this dissertation will supplement the ongoing recovery study regarding recovery in Lumberton after consecutive flooding events caused by 2016 Hurricane Matthew and 2018 Hurricane Florence, during which much of the case study data used in this project was collected.

1.4 Dissertation Outline

There are three major chapters within the body of this dissertation, beginning with a literature review of historical research conducted in the realm of community-level resource management in disaster scenarios. Also included in this literature review are historical flood-specific research projects, including hazard simulation techniques in addition to flood disaster mitigation and recovery investigations. A brief review of research relevant to the flooding events in Lumberton, NC, was also completed to accompany the case study portion of this dissertation.

Finally, some evaluation and decision-making tools were also examined to inform the relevant step in the framework.

In Chapter 3, the Societally-Optimized Resource Distribution framework is introduced. Each of the six steps making up the framework are individually discussed, exploring the potential options and constraints that may arise in each of these steps. The examination of the framework and its intricacies is applicable for most hazard types, though some emphasis is placed on flood-type hazards.

An overview and discussion of the Lumberton case study follows in Chapter 4. This chapter walks through the procedure undertaken to complete the case study, following the six steps introduced in the previous chapter. Specific attention is placed on the collection of relevant data needed to conduct the Lumberton study, as well as on analyzing the social vulnerability of the Lumberton community. Examples of the optimization and evaluation steps naturally follows and caps off the case study chapter. Chapter 5 concludes the dissertation and describes the contributions made to the body of research by this dissertation, as well as the limitations of the work performed and recommendations for future continued work for or using this framework.

2. Literature Review

Community disaster resilience, being an expansive, multidisciplinary field of study, can be approached in numerous different ways. Community disaster resilience is approached from the contexts of flood disasters and resource management in this dissertation. Additionally, the interaction between community disaster resilience and societal fairness is scrutinized. Previous efforts in the research and implementation of community disaster resilience, as they pertain to flood hazards, resource management and societal fairness, are therefore explored in this chapter.

2.1 Community Disaster Resilience and Recovery

The multidisciplinary nature of community disaster resilience can make this concept difficult to interpret and evaluate. Adequate consideration must be made to each of the aspects of the community, both individually and as a system. In 2015, a systematic review on the models and tools used for assessing community disaster resilience was conducted (Ostadtaghizadeh et al. 2015). Ostadtaghizadeh et al. (2015) found in their study five distinct domains for community disaster resilience: social, economic, institutional, physical, and natural. They also described the importance of how community disaster resilience indicators were unique to individual communities, and accordingly how the determination of such indicators was the initial step in developing community disaster resilience. The authors of the review state that an operational and measurable community disaster resilience model had not yet been achieved due to the complexities in quantifying the relationships of the five domains in influencing resilience. They also recommend that measuring disaster resilience be performed at smaller local or community-levels, rather than at larger national or regional scales.

One of the key implementations of engineering in community disaster resilience is the quantification of resilience. For example, the resilience quantification framework, used to define resilience in Chapter 1, was proposed in the context of earthquake engineering (Bruneau et al. 2003). Chang and Shinozuka (2004) later adapted an existing earthquake loss estimation model to compare two seismic retrofit strategies and gauge the potential increase in community resilience. While Chang and Shinozuka (2004) were able to demonstrate the utility of resilience quantification in guiding disaster mitigation efforts, they conceded that loss estimation alone is not sufficient to properly appraise a community's level of resilience.

In 2008, quantitative models for estimating the social and economic consequences of natural hazards were proposed through a project from the Mid-America Earthquake (MAE) Center (French et al. 2008). These quantitative models were based on the conceptual model that physical damage can be translated into social and economic consequences through the 'lens of social vulnerability' briefly discussed in Chapter 1. The MAE Center framework indirectly built upon the methodologies proposed by Chang and Shinozuka, where loss estimation is first used to quantify the consequences of the hazard; the results of these loss estimations are then translated into the social and economic consequences. The 'PEOPLES' framework for the measurement of community disaster resilience was proposed later in 2010 (Renschler et al. 2010). The PEOPLES framework identifies seven dimensions of community disaster resilience that are needed in the development of resilience measurement models; population and demographics, environmental/ecosystem, organized governmental services, physical infrastructure, lifestyle and community competence, economic development, and social-cultural capital. As can be discerned from this list of principles, classical structural engineering contributes to only one of the principles (physical infrastructure) in the multi-disciplinary framework.

From the many studies of *measuring* community disaster resilience came the idea of *setting goals* for disaster resilience, for instance to link disaster resilience goals to specific performance targets (Mieler et al. 2015, NIST 2016). A framework presented by Mieler et al. (2015) essentially works in the reverse direction as the previous studies in that resilience goals are set first, then built environment performance objectives are established afterwards, and lastly the built environment performance objectives (at the building-level) can be designed for using civil engineering. The National Institute of Standards and Technology (NIST; 2016) published a two volume Special Publication 1190, the Community Resilience Planning Guide for Buildings and Infrastructure Systems. The guide uses a six-step planning process for creating and implementing a plan for identifying, prioritizing, and managing the risks of hazards. The third step of the process explicitly includes determining community-level goals and objectives.

Resilience has commonly been considered to be most relevant at a community-level or greater. However, Lin et al. (2016) proposed the idea of first de-aggregating risk and resilience goals to establish performance objectives for individual buildings, as they argued that a community cannot be resilient if the individual actors (in this case, buildings) within said community are not resilient themselves. Tonn and Guikema (2018) expand on the concept of modeling individual buildings through their research in agent-based modelling for community flood risk. Their agent-based model combines the behavioral characteristics of households (agents) and engineering characteristics of their housing units to model flood risk perception and effects of community flood mitigation projects on each agent.

As with community resilience, community recovery has also been modeled using engineering for disaster scenarios. Early on, Chang and Miles (2003) proposed a comprehensive (conceptual and computer) model for community recovery. Their disaster recovery conceptual

model highlighted the interactions between households, businesses, and lifelines in the community, and was exemplified through a prototype simulation of recovery in Kobe, Japan after the 1995 Kobe earthquake. The Kobe case study defined four simulation zones using income and building-level mitigation, and considered the availability of short-term housing, water sources, and mutual aid agreements between zones. Later, Paton et al. (2015) further examined the efficiency of community recovery as a function of both physical impacts as well as the social environment in the context of earthquakes. In the realm of floods, Sutley et al. modeled housing recovery using a regression analysis of empirical disaster data, which combined physical damages with socioeconomic characteristics (household race and ethnicity, and receipt of financial assistance) to estimate repair completion and home re-occupancy (Sutley et al. 2019). Engineering can also be used to develop tools and functions to quantify recovery, such as building restoration functions for community recovery after tornadoes (Koliou and van de Lindt 2020).

The use of optimization in designing for community resilience is not a novel concept. In 2015, a methodology for optimizing seismic retrofits at the community-level by prioritizing social vulnerability and human consequences was proposed (Jennings et al. 2015, Sutley et al. 2017). The framework presented in the cited methodology used a multiple-objective optimization procedure which considered both engineering and socioeconomic variables to quantify the resilience of a community. Zhang and Nicholson (2016) built upon the previous work to consider the trade-offs between direct economic loss and population dislocation in their multi-objective optimization model. Later, Feng et al. (2017) presented another quantitative framework for retrofit optimization, this time considering the impacts of the intersectionalities between different building sectors (housing, education, business and public service) in a community. A similar framework was proposed by Gudipati and Cha (2019), which opted for community resilience-based design

optimization of seismic retrofits, this time accounting for the functional interdependencies between individual buildings. However, none of the optimization-based methodologies proposed thus far appear to have explicitly considered societal fairness, especially equity, as the primary optimization objective in a flood scenario for community resilience design.

Most recently, Baecher et al. (2019) presented a set of principles to use when guiding next-generation engineers in what they considered as resilient engineering. The article by Baecher et al. purposefully discusses how the role of engineers should change when designing resilient infrastructure, within the context of hurricanes and flooding. Their proposed first principles of resilient design extend beyond the reach of current building codes, which they deem insufficient as they do not account for the uncertainties of the future, such as due to the impacts of climate change. In addition to incorporating uncertainty into resilient engineering design, Baecher et al. suggest the integration of the physical and social domains of a community, designing at a systems-level, and the explicit inclusion of adaptability and alternatives in structural design decisions, including those nonstructural and nature-based. The idea that it is not only physical system which cope with disasters, but the individuals and organizations of the affected communities as well, is perhaps the key adjustment in how engineering can contribute to the design of resilient communities.

2.1.1 Societal Damage Indicators

Societal damage indicators are characteristics of a society (i.e., community) which can be used to predict or estimate the societal damage sustained by said society. The quantifiable version of these indicators are referred to as societal damage metrics. These indicators and metrics can find use in risk management strategies, evaluation of flood control measures and flood vulnerability assessments, among other similar types of study. Therefore, understanding which

societal damage indicators are applicable for a community and hazard type combination is necessary, as is setting metric values appropriately in a community's context. Indeed, Messner and Meyer (2006) published a book chapter arguing the lack of regard for socioeconomic factors in the then-contemporary flood damage analysis methodologies. Intangible flood effects, and indirect or second-order effects were also specified as lacking in these methodologies.

Within their discussion, Messner and Meyer also described several indicators as examples of potential drivers of vulnerability in flood-prone socioeconomic (and ecological) systems. The indicators were categorized into 'element-at-risk', 'exposure' and 'susceptibility' indicators; the first two described the damage potential and the hazard, respectively, whereas the latter more closely related to what is termed as societal damage indicators in this dissertation. Messner and Meyer listed several potential 'social susceptibility' indicators, including those pertaining to the preparedness, coping and recovery capabilities of households and local governance Example social susceptibility indicators included having flood insurance, the presence and quality of physical flood mitigations, the number of available emergency responders, and the preparedness and quality of disaster management organizations. Additional general socioeconomic indicators, including many demographic (census-related, e.g., age, poverty, race) characteristics, and infrastructure and lifeline susceptibility were also specifically identified in their book chapter.

The determination of social vulnerability to floods, and the merging of socioeconomic and physical features for flood vulnerability and risk assessment methodologies, now appears to be quite prevalent, albeit done in different manners (Simonović 1999, Tapsell et al. 2002, Scheuer et al. 2011, Cutter et al. 2012, among many others). Simonović (1999), through an examination of heavy flooding in Winnipeg, MB which occurred in 1997, recommended twenty-two social criteria to be used when evaluating flood management decisions; among these criteria included financial

burdens and loss, evacuation needs, physical and mental health, security, knowledge dissemination, and perhaps most related to this work, equity in levels of protection, share of flood consequences, and rights across the flood-affected region. Walker and Burningham (2011), from the United Kingdom, pointed to age, gender, income, pre-existing health conditions and belonging in a minority group as major indicators of inequitable vulnerability to floods. Johnson et al. (2007) added their observations of how flood risk management in the UK, informed mainly by economic benefit-cost analyses, fails to exhibit a sense of procedural equity. Scheuer et al. (2011) approached the social dimension of flood events in a different manner, in their case modelling social coping ability as a function of available social and health infrastructure and social networks.

Tapsell et al. (2002) proposed a composite-additive Social Flood Vulnerability Index. This index combined the Townsend Index indicators of financial deprivation, being unemployed, overcrowding, non-car ownership and non-home ownership (Townsend et al. 1988), with additional indicators for long-term illnesses, single parents, and the presence of elderly residents. Tapsell et al. also proposed in their paper the identification of especially vulnerable social groups, such that tailor-made flood management policies can be created for them. Cutter et al. (2003) also proposed the development of a composite index, the Social Vulnerability Index (SoVI), to integrate social vulnerability into federal flood risk management (Cutter et al. 2012). The SoVI used thirty-two socioeconomic variables, data for which was collected through the U.S. Census, to determine a relative measure of social vulnerability of geographical regions at the county-level.

Some algorithms specifically for the estimation of post-disaster population dislocation have been developed empirically (Lin 2009). The dissertation by Lin integrated tax appraisal data and census data with the data collected from a population impact survey conducted in 1993 in South Dade, FL. The target type of societal damage in Lin's study was probability of household

dislocation, and used structural damage, housing type (e.g., single family versus multi-family dwelling) and race and ethnicity as the societal damage indicators. Both household-level and neighborhood-level societal damage indicators were considered in Lin's statistical analysis; structural damage and housing type were found to be significant at the household level, while race and ethnicity (Black and Hispanic, specifically) were significant as a neighborhood characteristic.

Though many different socioeconomic factors have been used historically as societal damage indicators, there is still a gap in using societal fairness or social justice as an objective in flood management. Many historical studies have identified the importance of societal fairness in flood risk, resilience or recovery management, and current trends in social justice in the context of floods worldwide (Simonović 1999, Tapsell et al. 2002, O'Neill and O'Neill 2012, Thaler et al. 2018, Lebel et al. 2012, Sayers et al. 2018, among others), but the philosophy of societal fairness in resource distribution has not yet been methodically implemented into an actionable procedure for flood mitigation and recovery planning.

2.1.2 Resource Management for Disaster Recovery

The disproportionate impacts of disasters on relatively vulnerable populations, previously regarded as the 'lens of vulnerability', has also been observed to be intensified by inequitable resource distributions.

Resource management for large-scale disasters is often performed through governmental actions. Unfortunately, it has been suggested that recent developments in resource management for both flood resilience and recovery has been tending towards inequality. For instance, Muñoz and Tate (2016) performed statistical economic modeling in three Iowan cities following flooding in 2008 and found drastic ranges in federal funding provided to homeowners as a function of

property value. Regression analysis performed by Muñoz and Tate found significant negative correlations between certain social demographics and their proposed Relative Recovery Ratio, namely for Hispanic and elderly households.

Recent changes to the NFIP, a federally managed flood resource, were also identified by Shively (2017) to have social justice implications. Shively argued that changing NFIP policies, which have been historically subsidized, to become risk-based may cause substantial hardship for lower-income households living in flood-prone regions. Others have also identified potential inequities in governmental disaster resource management, including that of FEMA, which are driven by politics (Morrow 1999, Stehr 2006, Garrett and Sobel 2007). Other, non-political factors can influence inequalities in access to resources. For instance, Cutter et al. (2003) refer to socioeconomic status, language and culture as being potential stumbling blocks in accessing disaster funding or other types of resources. Studies following 2005 Hurricane Katrina (Elliott and Pais 2006, Finch et al. 2010) and 1992 and 2008 Hurricanes Andrew and Ike (Peacock et al. 2015) further demonstrated inequities in securing resources for post-disaster housing recovery, also driven by pre-event disparities is in socioeconomic (race, income, age, etc.) demographics. Similarly, these trends of inequitable access to disaster aid and subsequent recovery progress was echoed in data analyzed after in-land flooding caused by 2016 Hurricane Matthew in Lumberton, North Carolina, a particularly low-income community (Sutley et al. 2019).

The imbalance in the resource management of insurance payouts has also been criticized (Godschalk et al. 2009). Disaster impacts are disproportionately distributed based on pre-event conditions; insurance payouts act the same way. There is clear inequity in how pre-event wealth allows for not only a greater standard of living, but also greater access to resources (in this case,

affording insurance), as well as larger insurance payouts as they are proportional to the worth of the property.

Adger et al. (2005) expanded the scope of resource distribution to consider the concept of adaptation in ecological, social and economic systems. Two forms of adaptation were suggested: building adaptive capacity (increasing the ability of individuals or organizations to adapt), and implementing adaptive decisions (e.g., increasing reservoir capacities, planting hardier crops). They argued that for adaptive strategies to be successful, they must not only be effective and efficient, but also include elements of equity and legitimacy. In this case, equity referred to the fairness of the outcomes to those impacted by the adaptation, and legitimacy was the acceptance of the strategy by everyone, whether they are affected or not. In the study by Adger et al., focus was placed on adaptation to climate change, though the principles offered can be naturally transferred to disaster preparation and resilience.

Despite this body of knowledge illustrating the criticality of equity for disaster resource management, evidence of its direct implementation into the evaluation of resource management strategies is difficult to find. For example, benefit-cost analysis (BCA) is a commonly used tool to evaluate the cost-efficiency of a project. Many types of societal damage have been regarded as costs (or the inverse as benefits), such as injury, loss of life, community disruption, and changes in risk perception (Ganderton 2005). However, the BCAs conducted for disaster risk reduction and resource management typically aggregates all these costs and benefits as quantities representing the project, and all the population involved, as a whole (Shreve and Kelman 2014, Mechler 2003, Cardona et al. 2008, Kull et al. 2013, among others). Therefore, the individual benefits and costs, which has been shown to be magnified by pre-existing conditions and personal demographics, are hidden.

2.2 Flood Disaster Mitigation and Recovery

2.2.1 Mitigation Strategies and Selection

A significant amount of literature available for flood mitigation in the United States have been published by FEMA. For instance, FEMA specifies criteria for land management and use to meet requirements for the National Flood Insurance Program (NFIP), and also provides some requirements and guidance for building-level flood proofing. FEMA TB-3 and TB-7 technical bulletins are used to certify buildings for floodproofing for the NFIP (FEMA 1993a, 1993b). Extensive guidance for flood risk reduction, such as through home retrofitting and building utility protection, are also provided, such as through FEMA documents P-312 and P-248 respectively; additional relevant documents are also cited (FEMA 2008, 2011, 2013, 2014b, 2017). Flooding is also specifically considered for design in structural engineering codes and standards, such as through Chapter 5 of ASCE 7-16, Minimum Design Loads and Associated Criteria for Buildings and Other Structures, and ASCE 24, Flood Resistant Design and Construction (ASCE 2014, 2017).

Structural retrofits to buildings, in the forms of elevating entire home buildings and constructing elevated platforms inside business buildings, were used later in this dissertation. However, these retrofits are not the only options that have been studied for flood mitigation. Particularly, terrain management and conservation has been investigated (Brody and Highfield 2013, Kousky and Walls 2014). Brody and Highfield (2013) undertook a nation-wide study on the use of open space protection, a strategy which uses zoning provisions and land acquisitions to secure and maintain open spaces within local communities. While Bengston et al. (2004) noted that open space zoning had been traditionally used in these communities to provide recreation opportunities and environmental protection, Brody and Highfield identified a relatively recent trend of using open spaces for flood mitigation in the United States. Using a cross-sectional time

series, Brody and Highfield were able to isolate and identify the significant effect of open-space protection on reducing flood damage over time, suggesting annual savings of $200,000 per community. Kousky and Walls (2014) tightened the scope of their study on floodplain conservation as a flood mitigation strategy to the county- and parcel-level in St. Louis County, MO. The flood damage mitigation estimation was done in their study using a loss analysis procedure defined in the flood technical manual for Hazus-MH (FEMA n.d.). Their cost and benefit comparison showed that the opportunity cost was over twice that of the avoided flood damages alone, but significant additional benefits could be accrued through an increase in home values.

A trend towards promoting local-level action for flood mitigation was identified by Few (2003) in their review of research for the flood vulnerability and capacity of households and communities. Later, Brody et al. (2009) performed an evaluation of both structural and non-structural strategies adopted for flood mitigation by local decision-makers in Texas and Florida. This study did not necessarily evaluate the effectiveness of these strategies for mitigating flood damages, but rather measured which strategies were used, and how often they were used. Nineteen different flood mitigation techniques were identified, though notably building elevation was not one of the five structural strategies (or fourteen non-structural strategies) considered in this study. Instead, in the localities considered by Brody et al., retention ponds and debris clearing were the most extensively used structural strategies, while levees, dams and channelization were used less often.

Moser (1994) presented an overview of some traditional selection approaches for choosing flood control alternatives based on economics. Included in Moser's review was using cost-effectiveness, benefit-cost analyses, and multi-criteria analysis techniques. Many research studies

concentrated on the use of multi-criteria evaluation techniques in particular for flood mitigation planning (Reitano and Rossi 1994, Maragoudaki and Tsakiris 2005, Su and Tung 2014, Musungu et al. 2014, Jia et al. 2016, Rodriguez 2016); indeed, a full review of the state of the art for this area of study has been previously conducted (de Brito and Evers 2016).

For modeling the efficacy of flood mitigation strategies, hydrological modelling can also be appropriate. Reza (2007) illustrates the use of hydrological modelling for this purpose to evaluate structural and non-structural flood control practices, including land use change, applied in a case study for Kan watershed in Iran. The hydrological modelling was done using the HEC-HMS model supplied by the U.S. Army Corps of Engineers; the peak flood discharges and the time lag between peak flood discharges for 25 and 100-year return period events was able to be calculated. The hydrological modelling was also paired with the Simple Additive Weighting multi-criteria evaluation technique to choose the optimal flood mitigation alternative.

A sustainability-based assessment method for flood mitigation projects has also been proposed (Shah et al. 2017). This method used a combination of life-cycle analysis and multi-criteria analysis to establish sustainability criteria and indicators (e.g., changing the characteristics of the flood, contributing to environmental protections and social development in the floodplain, enhancing public policies), and subsequently to determine a sustainability index for various flood mitigation projects.

While a substantial variety of different metrics and analysis methods have been used for choosing or optimizing flood mitigation strategies, none have been found using societal fairness specifically.

2.2.2 Societal Damages and Inequalities

One of the most significant natural hazard events to have happened in the United States was the landfall of Hurricane Katrina in 2005. Katrina was not highlighted here only due to the immense economic damages which occurred as a result of the flooding of New Orleans, LA, and surrounding areas, but also due to the societal damages and inequities that entered the limelight in the aftermath. Despite the evacuation of over 1.2 million people from coastal Louisiana and Mississippi, over 1,800 fatalities were reported as a result of the hurricane. The United States Government Accountability Office (GAO; 2008) estimated a loss of 300,000 homes due to Katrina. Among these homes lost include public housing properties which are used by some of the most vulnerable population members. A news article published in The Guardian described the loss of public housing, where 3,000 of 7,200 homes were demolished after Katrina, and replaced with 1,829 privately-owned homes (Robbins 2017). The same trend was observed in Texas after 2008 Hurricane Ike and North Carolina after 2016 and 2018 Hurricanes Matthew and Florence (Hamideh and Rongerude 2018).

Petterson et al. (2006) conducted a preliminary assessment of the social and economic impacts stemming from Hurricane Katrina, finding evidence of misappropriation of recovery resources and the exacerbation of existing social trends and cultural distinctions. The latter perhaps be most exemplified by the shooting incident on Danziger Bridge. In terms of resource distribution, particularly highlighted was the emergency response around the Superdome, which was used to house hurricane victims, where water, food, space and security were all lacking. Laska and Morrow (2006) called Katrina an ‘unnatural disaster’, a disaster caused by the social processes and structures in New Orleans existing prior to landfall. Inequality and social justice were highlighted by Laska and Morrow as the fundamental drivers which inhibit the development of disaster

resilient communities. Myers et al. (2008) later investigated the relationships between place-based social vulnerability and disaster-induced migration, based on the trends found in the U.S. Gulf Coast after Hurricanes Katrina and Rita, the latter also having made landfall in 2005 with even greater wind speeds. Again, the same common trend was found where disadvantaged populations were impacted more severely, and were more likely to migrate away from their home communities after the two hurricanes.

One of the many recent high-profile flooding events followed 2017 Hurricane Harvey, particularly in Greater Houston, TX. Poor land use planning, and a general lack of zoning code, had been attributed as a major cause of the Houston floods, including in an article published by the Lincoln Institute of Land Policy (McCormick 2018). Widespread urbanization and development into the floodplains of Texas, in combination with climatological trends, were suggested to have substantially increased the intensity of the floods, measured by an increase in peak discharge at stream gauges of 84% (Sebastian et al. 2019).

However, just as was the case in Katrina, injustices were found in the Houston floods. Several studies investigated environmental justice in the metropolitan area by comparing the level of flooding to socioeconomic demographics. Statistical analyses found significantly greater extents of flooding in neighborhoods with greater proportions of non-Hispanic Black households and those neighborhoods with socioeconomically-deprived residents (Chakraborty et al. 2019a, Collins et al. 2019), in neighborhoods with residents with cognitive or ambulatory disabilities (Chakraborty et al. 2019b), and higher bankruptcy rates in flooded areas versus those that were not (Billings et al. 2019). One of the flood mitigation solutions employed by Harris County, where Houston is located, is a buyout program which is funded both locally and federally and designed to remove households and homes from the susceptible floodplains. However, even these buyout

programs have been purported to face racial inequities, disproportionately targeting counties and neighborhoods with higher proportions of White households (Elliott et al. 2020).

Similar trends of societal inequalities in flood-induced disasters could be found following 2016 Hurricane Matthew. Of particular note is an ongoing technical investigation in Lumberton, NC, a city which was afflicted by flooding from Hurricane Matthew (and again in 2018 by Hurricane Florence). The NIST-funded study, conducted through the Center for Risk-Based Community Resilience Planning, aims to facilitate the development of a multi-disciplinary engineering-social science study protocol to link physical and societal flood damages to socioeconomic factors (van de Lindt et al. 2018). The report cited here, which discusses the first 'wave' of investigations in Lumberton for the longitudinal study, describes the study methodology and some initial findings regarding population dislocation. These initial findings included models to estimate household dislocation in Lumberton for the flooding resulting from Hurricane Matthew (van de Lindt 2020). From these models, it was found that race and ethnicity significantly influenced the probability of household dislocation, as did higher percentage of rentership in census blocks. These societal and demographic indicators, along with poverty, were also connected to the vulnerability of public housing residents specifically in Lumberton, in the form of housing damage and displacement duration (Khajehei 2019).

Small businesses were also examined in a similar fashion after both 2016 Hurricane Matthew and 2018 Hurricane Florence by Meeks (2019), who explains how small businesses qualified for fewer and less ideal (debt-based) economic resources compared to other recipients such as households and public facilities. Ongoing negative trends from prior to Hurricane Matthew, and exacerbated by Hurricane Florence, were emphasized as major factors in the difficulty of recovery for small businesses. Another case study, by Watson et al. (2020), examined

the effect of local community disruption on the probability of Lumberton businesses fully recovering after Hurricane Matthew. Customer loss, labor disruption, and childcare and school closures were all found to be statistically significant indicators for lowering the probability of full business recovery. Aghababaei et al. (2020) developed a Bayesian linear regression model for business recovery quantification and prediction. The Bayesian model considered four indicators (cease of operations, revenue recovery, customer retention, and employee retention) to describe the recovery state of businesses. Aghababaei et al. also considered and incorporated the effect of the interplay between local households and businesses into their quantification and prediction model, particularly through the connection between customer retention rate and local household recovery. The business recovery model was also exemplified within the context of Lumberton and Hurricane Matthew.

The impacts of Hurricane Matthew were not only seen in Lumberton. Over one-thousand miles south in Haiti, the Igarapé Institute examined the differences between the experiences of men and women after the hurricane (Kolbe et al. 2017). Highlighted in Haiti were differences in ongoing displacement, access to stable housing, proportions of household expenditures for food, and perceptions of international resource distribution to their home community.

Flooding is obviously not unique to the Americas. For instance, substantial research for flood mitigation and recovery has been published following the constant flooding in the Brahmaputra River Delta, where Bangladesh is located. A study performed as part of the Irrigation Support Project for Asia and the Near-East examined the floodproofing and flood protection methods used in Bangladesh (Thompson and Tod 1998). In that study, Thompson and Tod (1998) describe how the term floodproofing was extended beyond buildings to include community-level measures, such as the provision of flood shelters and raising the surface of roads to be above

expected flood levels. The study by Thompson and Tod further examined a region in Bangladesh on the banks of the Jamuna River, which flooded to levels of 1-in-50 to 1-in-100 year return periods in two cities in 1988, and again to 1-in-2 and 1-in-5 year turn periods in 1991. As a result of that study, Thompson and Tod argued that the poorest households would find the greatest benefits from floodproofing practices, largely due to the loss in income from loss of personal assets, labor and business downtime, and loss of usable land due to erosion resulting from flooding.

It was found in 2004 that socially constructed processes, driven by inequity in access to resources, pushed flood-induced displacees in Bangladesh towards additional socio-economic impoverishment and marginalization (Mutton and Haque 2004). Mutton and Haque (2004) also identified in their study that similar social and demographic factors contributed to the vulnerability to floods in Bangladesh as in the United States. These authors make the same hypothesis as this dissertation, in that hazard mitigation should account for societal and demographic inequalities. Another study of two particular villages in Bangladesh further emphasized this point, showing that more fortunate socioeconomic circumstances allowed for better coping in flood disasters (Paul and Routray 2009). Another study looked at the 1998 floods in Bangladesh, specifically towards famine and food crises (del Ninno et al. 2009), which are forms of societal damage that may not be commonly associated to floods in the United States due to a level of perceived food security nationwide. Del Ninno et al. found that, despite extensive losses of domestic food crops in 1998, no major food crises occurred in Bangladesh compared to historical flooding in 1974, due to public distribution practices and changes in food import habits. Unfortunately, despite the overall appearance of success of these distribution practices, the poorest households were again found to be disadvantaged, still needing to accumulate heavy loads of debt to afford nutrition.

It has been previously demonstrated that there are many strategies available for flood mitigation, both structural and non-structural, at the building-level and at the community-level. However, there has also been research conducted on who the major actors are, or should be, to implement flood mitigation practices. For example, Laska (1986) talked about the involvement of homeowners in becoming proactive in flood mitigation for their own properties. Research from earlier than 1986 had shown that homeowners did not actively participate in the flood protection of their property, though Laska argued that the trends were changing at the time of their article's publication. Publications somewhat more recently in 2001 and 2003, however, suggest that citizen involvement in the general development of hazard mitigation was again low (Affeltranger 2001, Godschalk et al. 2003, Hamideh and Rongerude 2018). Critically, Affeltranger (2001) points specifically towards the high diversity amongst stakeholders as a significant source of complexity for local level disaster mitigation strategy development, amongst other reasons. Few et al. (2011) further applies a similar argument to policy responses to climate change. Few et al. describes how the complexities that accompany having a wide range of stakeholders, especially those existing due to relative power dynamics, are amplified by the long-term, uncertain nature of climate change. Hamideh and Rongerude (2018) presented yet another issue plaguing public participation, where an inability of public housing inhabitants to participate was a result of social vulnerability. The study by Hamideh and Rongerude, based in Galveston, TX, after 2008 Hurricane Ike, found that a combination of three mechanisms was the source of this vulnerability: 1) the affected residents being physically displaced, 2) public housing being generally undesired and stigmatized, and 3) the consideration of the residents as housing units instead of human beings. Hamideh and Rongerude further noted how this situation was perceived as an opportunity to reduce public housing in Galveston, rather than to recover it. About 50 miles away, Rumbach and Sullivan (2018)

found the same absence of the ability to participate in public discussion in mobile home parks in the Houston area, following Hurricane Harvey. Mobile home parks often house socioeconomically disadvantaged households due to their relatively inexpensive costs. Unfortunately, these public discussions involving housing damage and recovery, in their absence, therefore lacked any discussion of specific resources or recovery plans for the mobile home parks.

The disconnect between acknowledging societal fairness and procedurally implementing it in disaster management has been shown. In fact, it has been shown that oftentimes societal fairness is eschewed altogether by decision-makers. Numerous historical studies have shown the criticality of societal fairness for disaster risk reduction, community resilience and resource management, but no evidence was found that societal fairness has yet been a major objective in the design of any of these disaster management policies. It will be critical to further promote societal fairness to decision-makers, but developing an effective way to implement the concept will be the first step.

3. Societally-Optimized Resource Distribution Framework

A multi-disciplinary framework for the development and evaluation of disaster management resource distribution strategies is presented in this chapter. This framework merges engineering analytical practices with social science metrics in order to produce socially-optimal resource management solutions. To do so, the framework adopts societal damage indicators to represent the characteristics and reactions of the community for which the resource distributions are being designed. Societal damage indicators more closely relate to the consequences experienced by the population of the community, but are difficult to implement in an engineering-based methodology purely dependent on physical sciences. Rather than relying solely upon structural engineering sciences, the societal damage indicators were brought into a multidisciplinary framework. A merger of civil engineering, sociology, policy making and planning research interpreted the societal damage indicators, and how they depict the combined effects of a natural hazard event and a resource distribution strategy on a community.

The main goal of the framework is to formulate resource distribution strategies which are not dependent on anecdotal evidence or inherently unjust principles. Namely, the resource distribution strategies should be designed with a specified and measurable objective; for those developed through the framework, the objective is some form of societal fairness.

Too often are decisions and policies made, including for disaster resource distributions, solely based on traditional practices. In other words, the distribution strategies currently used may be based on outdated data and social principles, despite the drastic evolutions that have occurred in how societies operate. Communities in the modern age are made up of a population, organizations and built environments that are adapted to new local cultures and contemporary technologies. In the very same way, resource distribution strategies should be optimally driven by

modern, locally-appropriate data; this becomes the impetus for this dissertation which offers a novel Societally-Optimized Resource Distribution (SORD) framework.

The SORD framework consists of six major steps, shown in Figure 1, which include scenario development, data collection, optimization, and decision-making. As the user progresses through the six steps of the framework, the resource distribution strategy is designed to become more and more customized to the qualities and needs of the community at hand. The following is a simplified narrative breakdown of each of the six steps; a detailed discussion on each step in the SORD framework is presented starting in Section 3.1.

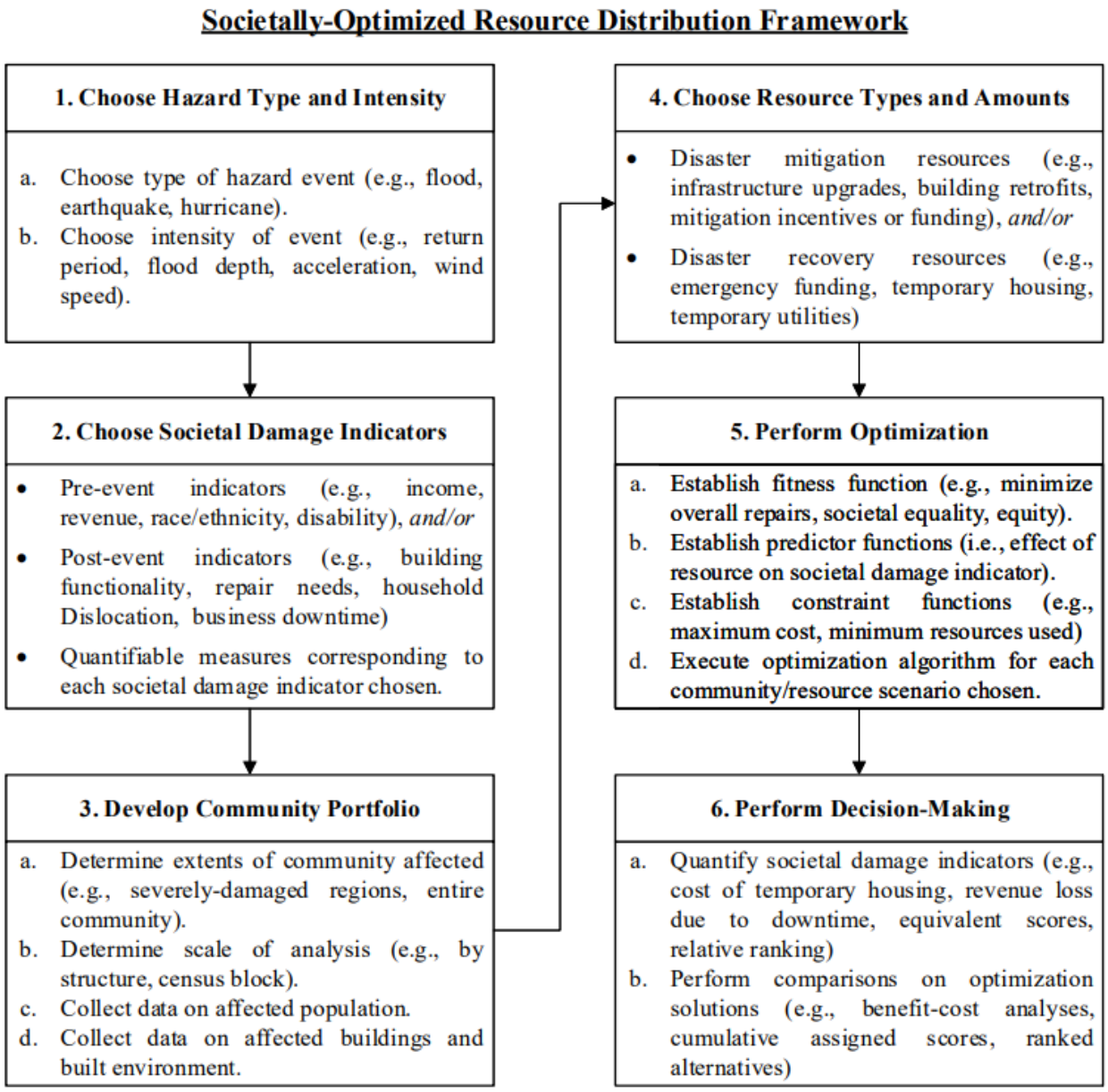

Figure 1. The six steps of the Societally-Optimized Resource Distribution (SORD) framework.

1. First, the parameters of the hazard in question are chosen by the user. At minimum, these parameters should include both the type and intensity of the hazard. This hazard will be an acute event with a significant probability of causing substantial damages to the community.

2. Second, the societal damage indicators desired to evaluate the eventual solutions must be chosen. Depending on the anticipated availability of locally-relevant data, these indicators may consist of one or more characteristics of the community at a non-disaster condition ('pre-event'), or those that result from the occurrence of the hazard event ('post-event'). Quantifiable societal damage metrics corresponding to the indicators chosen will then need to be established for use in the mathematical optimization in step 5.
3. The community-in-question is then characterized in the third step. This is done by first performing a physics-based simulation of the chosen hazard event in the target community. The spatial scope, or the geographical extents, of the resource distributions can then be determined from the simulation results. Real-world data that is pertaining to the societal damage indicators chosen in the second step must also be collected for the portion of the community within this geographical zone, so that the community can be accurately characterized.
4. The scope of the resource distribution strategy development is finalized in the fourth step. Here, the user chooses which types of resources are available and are most appropriate for the disaster scenario. These resources may be those that are implemented ahead of the hazard event (for mitigation) or after the hazard event (for recovery), and can take any form (e.g., physical solutions, organizations and processes, monetary).
5. Optimization of the resource distribution strategies are performed in step 5. In order to conduct the optimization, three types of functions are necessary. Predictor functions are necessary to determine the effect of the chosen resources on the

societal damage indicators. A fitness function is paired with these predictor functions, which determines when the calculated values for the societal damage metrics meet the criteria for societal fairness. Constraint functions will define limits to confine the solutions within a feasible space. Finally, an optimization algorithm should also be chosen in this step, and then be executed using these three functions and the parameters chosen in steps 2 through 4.

6. The final step includes the evaluation of the optimized solution(s). The resource distribution strategies obtained should be evaluated to not only see if they are economically feasible, but if the outcome of their use sufficiently meets the societal fairness objective used. If steps 1 through 5 are run multiple times for different combinations of hazard intensities and resources, the best solution or solutions must be chosen for implementation. One common method of comparative evaluation is to use benefit-cost analyses, which yields an easily comparable metric (benefit-cost ratio) for each solution. However, the decision-making tool adopted in this step is up to the user.

A brief outline of the SORD framework was provided above; the following sections delve deeper into each step. The necessities and constraints for each step are further detailed and are paired with some potential choices or suggestions for the readers' consideration.

3.1 Hazard Classification

Generally, community planners and decision makers are aware of the types of hazards that threaten their community. Such hazards may be naturally-occurring, or may be the result of human activity. Naturally-occurring hazards are dependent on the local meteorological and geographic features. Thus, given the wide variety of climates and geographical features across the United

States, American communities are subjected to many types of natural hazards. Fortunately, the direct effects of many of these hazards, on buildings and other structures, have been quantified in some fashion within published building codes and standards.

The SORD framework is currently intended for relatively short duration, natural hazard events. Natural hazards of this type include floods, hurricanes, tornadoes, earthquakes, tsunamis, wildfires and blizzards. The effect of long-term hazard events, such as extended droughts or economic downturn, on the community can vary over the hazard's duration, which means that the analysis and solutions must be represented as a function of time. Guidance for time-iterative analysis of the cycles of hazard impact, resource distribution and partial recovery has not been included in the current framework. Another type of hazard are human driven hazards. Some examples include industrial accidents, engineering or construction failures, and acts of terrorism. If their impact on the built environment can be simulated and the resulting effects on the community population are sufficiently measurable, the SORD framework may also be implemented for human driven hazards. Pandemics and socio-political unrest are outside the scope of the SORD framework given their impact on the functionality of the built environment is limited.

When choosing the type of hazard to address within the SORD framework, it is critical to understand one's ability to accurately model the effects of the hazard in a community. In other words, the main limiting factor in this first step is the necessity to simulate the hazard event later in the procedure. Physics-based models can be adopted or developed if the expertise is available. Computer simulation platforms also exist for modeling the effects of natural hazards on built environments, such as OpenSHA for earthquakes and the U.S. Environmental Protection Agency's SWMM for floods. FEMA's GIS-based Hazus program is also highlighted here for its ability to estimate physical damage as well as economic and social losses for hurricanes, floods, wind and

earthquake hazards. The issue remains, however, that if the chosen hazard is not able to be simulated, then it will be implausible to use this framework.

Accordingly, the hazard type(s) and intensity(s) must therefore be defined sufficiently, so that it can be properly simulated in step 3. The type of hazard should be adequately defined, especially for natural hazards. For example, consider a hurricane event. The physical mechanics of hurricanes will not differ greatly from another, but the impacts on communities can. Depending on the location of the community, one would consider varying intensities of straight-winds along with wind-driven rain. Additionally, storm surge will be a possibility if the region in question is coastal, or riverine flooding if the community is built on floodplains. The intensity of earthquakes similarly depends on the location of the community, and can also be accompanied by secondary hazards as such as tsunamis or landslides. Flooding hazards may need to be differentiated between coastal, riverine and pluvial floods, since their mechanics can be significantly different in terms of flood height, duration and wave velocity (among other characteristics).

A common method of indicating the intensity of a natural hazard event is by defining its return period. This description provides some additional context to the risks surrounding the event by specifying the probability of such an event occurring in a given time period. Guidance exists for communities to access pre-determined intensities correlated to different return periods for natural hazards occurring in their localities. For example, the ASCE 7-16: Minimum Design Loads and Associated Criteria for Buildings and Other Structures standard uses, as the basis for wind load calculations, 3-s gust wind speeds corresponding to return periods of 1.7% to 15% probability of exceedance in 50 years, depending on the structures' perceived Risk Category (ASCE 2017). Other values that are similar in function to return periods include annual exceedance probabilities and mean recurrence intervals, and can also be used for hazard intensity selection.

When defining the type of hazard for flood events, it is prudent to also specify the type of flooding for which the resource distribution is being designed for. The differences between coastal and riverine flooding, for instance, will need to be addressed in step 3 when the event is being simulated.

For flood-type hazards, the FEMA National Flood Insurance Program uses a return period defined as the 100-year flood (a flood intensity which has a 1% chance of occurring or being exceeded each year) for the 'base flood' when creating flood zone maps (FEMA 2019a). The same return period, or base flood, is presently used in the ASCE 7 standard, and has been since 1995 (ASCE 2017). Given that the FEMA-managed flood insurance program relies upon these flood zone maps, the 100-year return period is highly recommended as a starting point when defining the hazard intensity.

3.1.1 User Recommendations

When using the SORD framework, most users will already have a particular hazard type in mind. It is common for a community to have a key, "high profile" natural hazard associated with it, such as hurricanes for cities on the east coast of the U.S., earthquakes for those near known fault lines, and flooding in cities residing on riverbanks. The possibility of that type of hazard occurring is also often taken as inevitable. The more difficult decision is determining when that "inevitable" hazard will take place, or in other words, determining a return period for the hazard.

Historical records of natural hazards in the local area can help the user in choosing the hazard intensity or return period. These records can be particularly desirable not only because this information is contextual to the community, but also because they may be accompanied by useful data describing the properties of the historical incidents. Numerous natural hazard databases exist,

such as NOAA's National Centers for Environmental Information, the earthquake records of the United States Geological Survey, and the US Natural Hazards Index hosted by Columbia University.

Where appropriate, multiple hazard intensities may be considered in parallel using this framework. Doing so allows the user to make risk-based (probabilistic) decision-making, and determine what return period can be the most appropriate, based on cost efficiency for instance. Similarly, the framework results from multiple hazard *types* could also be compared to identify the critical hazard(s).

3.2 Societal Damage Indicators

In the same fashion as the hazard type and intensity, the societal damage indicators adopted for use with this framework must be able to be quantified as societal damage metrics. What is critical when choosing the metric which corresponds to the societal damage indicators is that the measures must be mathematically representable within a function, since computational optimization will be used later on in the procedure outlined by the SORD framework.

As shown in Figure 1, pre- or post-event societal damage indicators may be used within the framework. In terms of obtaining the relevant data for the United States, some of the most accessible pre-event societal damage indicators will be those reflected in the census data collected by the United States Census Bureau. The Census Bureau conducts numerous surveys at regular intervals (from quarterly to decennial) to collect information regarding many community actors, such as households and businesses. Census data includes many indicators that have been examined in previous studies by others (Cutter et al. 2003, Jennings et al. 2015, Peacock et al. 2015, Muñoz and Tate 2016, Chakraborty et al. 2019a, Elliott et al. 2020, among many others). Some notable

examples for households include race and ethnicity, income, age of occupants, and home occupancy status (renter- versus owner-occupied).

The United States Census Bureau operates the OnTheMap web-based application (https://onthemap.ces.census.gov/em/) to aid emergency managers in identifying the characteristics of their local populations. The types of information provided in this web-based tool can be used as pre-event societal damage indicators, and are as follows (USCB 2020):

- Race, and Hispanic or Latino Origin
- Ability to Speak English by Age and by Language Spoken at Home
- Disability Status by Poverty Status and by Age
- Poverty Status and Ratio of Income to Poverty Level in the Past 12 Months
- Population 65 Years and Over Living Alone, and Households with One or More People 65 Years and Over
- Earnings, Social Security Income, Supplemental Security Income, Public Assistance Income, and Retirement Income in the Past 12 Months for Households
- Households Receiving Food Stamps/SNAP (Supplemental Nutrition Assistance Program) in the Past 12 Months
- Year Structure Built, and Aggregate Value of Owner Occupied Housing
- House Heating Fuel
- Mobile Homes
- Vehicles Available

Some common post-event societal damage metrics include household dislocation duration, business downtime duration, home or building functionality loss (beyond solely physical damage), cost and time to repair, and capacity to recover.

There are many types of post-event societal damage indicators that are relevant to floods. Flood damages extend beyond those immediately dealt to the built environment, and includes societal, physical health and psychological damages in affected households (Convery and Bailey 2008, Gray 2008, Lamond et al. 2015). Long-term deterioration of building properties is another consequence of flooding (Eves 2002). Shifts in risk perceptions is another societal indicator that is not directly related to damage (Albright and Crow 2016). Many different societal damage indicators can be used for floods; the choice is predominantly controlled by the supporting data available.

One straightforward way of achieving societal fairness is by balancing the magnitudes of the post-event societal metrics. The issue, however, is the availability of such indicators and metrics.

The data for post-event societal damage indicators would typically come from historical disaster records. This unfortunately means that to collect 'perfect' data for a specific community and hazard type and intensity, the event must first occur in the community; clearly, this is an undesirable situation and should not be depended on. The logical alternative would be to use data from a similar hazard and community, if it exists at all. However, two major limitations exist in using this type of data. First, if the data comes from another community, it can only be partially relevant due to the inherent differences in the population and must be accompanied by this significant caveat. If the hazard intensity or other characteristics (e.g., secondary hazards) are different, then the effect on the community may be disproportional to the difference in intensity.

Second, the availability of up-to-date data from previous events is limited due to a lack of investigations and consistency across investigations. Many of the well-recorded disasters, such as the 1994 Northridge earthquake and 2005 Hurricane Katrina, occurred when different policies, technology, resources, and culture existed. Therefore, considering both limitations, most existing data will be either outdated or out of context to the modern setting. Rare exceptions can exist; as previously discussed in the literature review, Lumberton, NC, is an example to the contrary. The data and lessons learned from the flooding due to 2016 Hurricane Matthew were applicable when a very similar flooding disaster occurred due to 2018 Hurricane Florence, particularly due to the short amount of time between the disasters during which changes to the community would be limited.

Ultimately, if the data for representing post-event societal damage indicators is indeed available, it is encouraged that they be used. However, as noted in the outline of the framework provided earlier, the societal damage indicator is not necessarily required to reflect the condition of the community post-disaster. The consequences of a disaster event are expected to be some function of the pre-event conditions, which means they can be used in lieu of post-event conditions.

3.2.1 User Recommendations

The most crucial requirement in choosing societal damage indicators is to be able to sufficiently characterize the socio-economic inequalities across the community. Avoiding or ignoring these properties is wholly contrary to the purpose of the SORD framework. Therefore, it is important to have a fundamental understanding of the potential inequalities that *do* exist in the community. A recommended preliminary step is to develop this understanding, critically not on the basis of assumptions nor traditional expectations, but with modern, contextual evidence. Through this process, it should become more evident which socio-demographics most relate to the

inequities, such as race and ethnicity, income, or age (amongst many other possibilities). One possible method of doing so is to work with local community leaders, many of which will be quite familiar with these inequities and pleased to help address them. Town hall meetings and forums are other instruments for hearing the concerns of local constituents, but they also come with concerns of accessibility by socially vulnerable people, as noted by Hamideh and Rongerude (2018), and Rumbach and Sullivan (2018).

The second-most important societal damage indicators may be the physical properties of the community. The majority of the outcomes of the natural hazard will be driven by the interaction between the natural phenomenon and the built environment. Sufficient information about the built environment will also be necessary for an adequate simulation of the hazard using computational means. The state of the built environment can be informed by considering local building codes, taking account that older buildings will have been stipulated from older editions of the building code. Other options include door-to-door surveys, using vehicle-driven 360º cameras, and supplementing data with aerial/satellite imagery.

3.3 Community Portfolio

The goal of developing a community portfolio is to be able to accurately predict the portions of the community for which the resource distribution strategies should be designed for. The data needed to proceed with the framework is also defined in this step.

3.3.1 Target Population and Scale

Developing the community portfolio starts by determining the scope of the resource management. This scope can be defined in either geographical terms or by identifying certain groups of the community population. The former essentially sets physical boundaries or borders

within the community in question which may align with floodplains, coastlines, faults, etc., and sets the goal of the framework to achieving societal fairness across the population within these boundaries. This boundary serves to differentiate between the portions of the population directly or substantially affected by the hazard from those who are not, and should not act as a discrimination tool. This geographic-based scope determination is most applicable for small-scale or bounded hazards, such as for some flooding scenarios, especially in communities with substantial differences in elevation and proximity to bodies of water.

During the determination of the scope of the resource distribution strategies, it can prove highly beneficial to implement physics-based hazard simulations. By doing so, it will be made clear which portions of the community are most susceptible to the hazard of interest. Geographical boundaries can then be set easily using the results of the simulation. On the other hand, the most vulnerable groups of the community may also be identified using the simulation, assuming the physical and/or societal characteristics of the community was also implemented in the simulation. A review of contemporary flood hazard simulation methodologies is provided in the literature review located in Chapter 2. A scale should also be chosen once the scope of this development process is set. This scale describes the resolution of the data needed, and also how discretely the resources will be distributed (e.g., by building, block, or census tract). The scale will most likely be defined by the quality of the data available for the societal damage indicators. For any given scale chosen, some level of statistical analysis will be necessary to aptly represent each discretized portion of the population, or population element, in the scope.

3.3.2 Population Data

In addition to the data collected to describe the societal damage indicators, supplemental population data should also be gathered. This supplemental data should be used to provide greater

context when considering each element of the population. As much context should be employed while using the SORD framework, for example while calculating the effect of the hazard on each element of the population, determining their relative vulnerability or exposure to the hazard, predicting their capacity to recover, and when apportioning resources. The second volume of the NIST Community Resilience Planning Guide (NIST 2016) provides strong guidance in characterizing the community for these contexts.

Usually, whatever societal damage indicators that are not chosen in step 2 can make up the supplemental population data. However, it can reasonably be assumed that these types of characteristics (race/ethnicity, income, education) are not independent from one-another. An example affirming this assumption for a certain population of Lumberton, NC, is included in the following case study. If statistical analysis, such as a regression analysis, is to be conducted on these characteristics, one must take care to have explanatory variables which are as independent as possible from one-another. Correlation analysis can help determine the degree of interdependency between these characteristics.

The usefulness of potential supplemental data is controlled in part by the scale chosen earlier in step 3. Ideally, the supplemental data collected will be at the same scale, or finer, as the societal damage indicators. Each population element can become more uniquely defined and differentiated from one-another if this is the case. An example is the case where the societal damage indicators are adopted at a block group-level, and the number of children in each household within the block groups was obtained. The amount of detail describing the block groups can be enhanced by taking the mean or other statistical representation of the distribution, and assigning it to the block groups.

However, it can be challenging to obtain a relatively-fine dataset, such as one that exists at a household-level. For example, for the 2013-2017 American Community Survey 5-Year Estimates, the finest detail for annual household income in the State of Kansas was found to be at the block group-level (each typically containing between 600 and 3,000 people). If the planning resources permit, the user can choose to conduct their own research program to obtain relevant data at the resolution desired. Otherwise, the user may find it necessary to choose a larger scale to correctly use existing data.

Using high resolution data is not necessarily required, and in some cases, trends found in a large group of people could be 'smeared', or aggregated, across the multiple population elements that fall within that group. For example, if the average household size for a census tract is known, this average number could be assigned to each of the block groups that make up the census tract. However, while the purpose of the supplemental data is to represent each population element with as much potentially-relevant detail as possible, careful consideration needs to be made to not carelessly overgeneralize a population trait. This is especially important when dealing with generally secure populations with small pockets of vulnerable people. One possible way this could transpire is by observing a relatively-high average income for an entire community, and assigning it to the entire population. This generalization effectively ignores the disadvantaged people at the low end of the income spectrum, statistically balanced by the extremely opulent. Since the critical objective of this framework is to attain societal fairness, the depreciation of the vulnerability of the disadvantaged population is quite contradictory.

3.3.3 Built Environment Data

Building data, or data pertaining to any portions of the built environment of the community, can be used in a similar fashion to the supplemental population data. The human population of the

community is very much dependent on the built environment that surrounds them. This is even more true if particular buildings are highlighted, namely the home of a household, or places of employment and/or business (the combination of these two types of buildings likely covers the vast majority of buildings in a community). Some societal damage indicators, such as household dislocation, explicitly address this dependency.

Therefore, due to this dependence, connecting the building properties to their occupants is important. The structural characteristics of buildings inform the resulting integrity of the building after the occurrence of natural and physical hazards. The architecture of and systems used in the building defines how the building can be used during and after the hazard passes. These in combination can provide insight into the building's post-event functionality, and the cost and time needed for repairs. If a hazard simulation is being conducted as part of using the SORD framework, sufficient geospatial data regarding the buildings and built environment of the community will also be necessary.

Some building characteristics are essential in order to properly consider a flooding event. Primarily, the elevation of the floor of the building should be compared relative to the maximum expected floodwater elevation for the hazard intensity chosen. For many homes and some other buildings, this elevation can be informed by the type of foundation used (such as a crawlspace versus slab-on-grade). Many methods of flood mitigation are also applied at the building-level, and should also be considered appropriately. For most, if not all, flood hazard simulations, measurements of the geography (topography) of the community are also necessary; one source of topographical data that can be used is the National Map developed through the United States Geological Survey National Geospatial Program.

3.3.4 User Recommendations

One of the most accessible sources of relevant data in the United States will be that collected by the United States Census Bureau. The Census Bureau collects information using numerous different surveys and programs beyond the Decennial Census, particularly the American Community Survey (ACS; conducted annually and existing in 1-year and 5-year average formats), American Housing Survey (AHS; conducted every two years), and the Annual Business Survey (ABS; appropriately conducted annually).

However, inequity can exist at multiple scales, such as between neighborhoods of a community or between households in the same neighborhood. The scale of the inequity must match the scale of the data describing said inequities, which can be a difficult issue to resolve. For example, the Census Bureau does not collect household-level data; if the inequities in the community do exist at this scale, then supplemental data will need to be obtained use the SORD framework effectively. In the Lumberton case study which follows in Chapter 4, this supplemental data was collected using door-to-door surveys on a statistically representative sample of the households and businesses in the city.

3.4 Resource Inventory

With the details of the community or portions of the community being considered known, the next step is to choose the types of disaster management resources to include in a resource inventory. Much like for the societal damage indicators, this framework focuses on two relative time periods for distributing resources; the delivery of resources prior to the hazard event to mitigate potential damages, and after the hazard event to promote recovery. Note that many

resources will also need to be used *during* the occurrence of the hazard event; however, this is outside of the scope of the current SORD framework.

The many types of resources relevant for a particular hazard can be organized into many categories; in other words, resources can take many different forms. At the most basic level, there are 'fundamental' resources that can be used or transformed to obtain other specific resources. Money, or funding, is one of the fundamental forms of resource. Human resources ('manpower') is another fundamental resource. These fundamental resources, if distributed, allow for more control by the recipients to choose the type of mitigation or recovery they wish to pursue. Of course, they also come with the risk of waste if they are not accounted for properly or not used for the purpose of addressing the hazard event.

It may be the case that the resource provider wants greater control over the resources distributed and implemented to prepare or respond to the hazard event. For example, many funding agencies will require a detailed plan to be in place before providing the money to enact disaster management solutions. FEMA is among these agencies, requiring the submission and re-submission of hazard mitigation plans by jurisdictions at 5-year intervals to be eligible for FEMA's Hazard Mitigation Assistance grant programs.

Another reason that specific resource types would be chosen is to have a greater understanding of the outcomes of using those resources. Predicting how cash would be used by a wide variety of population elements is oftentimes impractical; on the other hand, one could predict, with far greater certainty, how spending the money installing a tornado shelter would affect hazard mitigation and disaster recovery.

Regardless of the reason, sufficient research should be done by the user to identify the most pragmatic mitigation or recovery solutions for their particular scenarios. If needed, the user can also choose to use the SORD framework to weigh the advantages and disadvantages of different resource types, within the context of societal damage.

If multiple types of resources are chosen to be optimized within a single strategy using this framework, the ability to quantify or compare between these types should be regarded, as well as accounting for any restrictions on use that may come with one or more resource types. Most, if not all, computational optimization algorithms will require some numerical relative value be assigned to each variable. The user does have some leeway in defining the value of these resources, though ultimately it should be consistent with the societal damage indicator(s) chosen. Some options for describing the value of a resource include its monetary cost to produce or implement, the amount of mitigation or recovery it provides, and the feasibility of implementation of said resource (e.g., aesthetic value, practicality outside of hazard events).

Once the types of resources to be included in the inventory are chosen, some decisions about the amount of each resource available must also be made. This process essentially defines the constraint functions that the computational optimization algorithm will use. These constraint functions could be removed; for example, the purpose of using this framework may instead be to determine *how much* resources is needed to achieve a predefined level of societally fair mitigation or recovery.

3.4.1 User Recommendations

The two main decisions that will likely need to be made at this step are the forms of resources provided (usually between providing monetary funds and providing specific products or

services), and when the resources are applied (pre- or post-event). Monetary funding is easier to distribute in a more granular fashion across a community compared to designed solutions (such as structural retrofits or buyouts) that require funds to be concentrated at fewer locations. However, the effectiveness of providing monetary support comes with more uncertainties on how it will be spent, versus knowing the effects of a designed solution on the outcomes of a natural hazard.

In the Lumberton case study explored in Chapter 4, retrofits targeted for flood mitigation were chosen as the resource. Other flood-specific resources for mitigation and recovery were discussed in-depth in the literature review contained in Chapter 2. Mitigation is particularly desirable since studies have shown that there are very high returns on each dollar spent ahead of the hazard, versus for recovery (Multihazard Mitigation Council 2018). However, mitigation does require the upfront investment of funds, which may be infeasible without external support (which, in turn, may unfortunately be easier to obtain only after the fact when news of the tragic consequences become widespread).

Recall that the SORD framework can be used to compare between scenarios if needed. In this case, multiple types of resources can be tested to see which provides the most equitable outcomes, or which provides equitable outcomes with the most other benefits (such as cost efficiency). These comparative results can serve as strong evidence for securing the funding for hazard mitigation projects, for instance.

3.5 Optimization

The societally fair resource distribution is developed using optimization. The genetic algorithm optimization conducted as part of the SORD framework requires the inclusion of three types of mathematical functions: (1) the fitness or objective function, (2) constraint functions, and

(3) predictor functions. The constraint functions should be defined in the previous step by establishing the availability of each resource.

The fitness function describes some inherent value of the system being optimized. Within optimization problems, the goal is usually to maximize (or minimize an inverse form of) the fitness function. Mathematically, this appears as:

$$f_{fit}(\boldsymbol{x_n}) \geq f_{fit}(\boldsymbol{x}) \text{ for all } \boldsymbol{x} \in S \text{ or } f_{fit}(\boldsymbol{x_n}) \leq f_{fit}(\boldsymbol{x}) \text{ for all } \boldsymbol{x} \in S \quad (1)$$

for maximization and minimization, respectively, where f_{fit} is the fitness function, x are options or alternatives in a set S, and $\boldsymbol{x_n}$ is the 'optimal' option. Consider 'profitability' as a classic example of a common fitness function in optimization problems that should be maximized.

In the SORD framework, the fitness function is the mechanism which enables societal fairness. This function describes the sameness or difference of the value of the societal damage metrics belonging to each of the population elements. In Equation (1), $\boldsymbol{x}$ becomes a vector of the societal damage values for all population elements considered, and $f(\boldsymbol{x})$ is in turn the sameness or difference between the values of $\boldsymbol{x}$. Depending on how the fitness function is written, it may need to be maximized or minimized (one can design the fitness function to be maximized in the optimization if they interpret the difference of societal damage value as taking the negative form of the magnitude of the difference, or vice versa). If multiple societal damage indicators were chosen in the second step, or if multiple hazard scenarios were selected in the first step, a "Pareto optimal" solution will be obtained. Thus, the societal damage indicators must be comparable in some logical manner.

Optimization procedures operate by 'searching' for an optimum within a solution space. However, the default solution space contains every possible solution, including those that may not

be feasible for some reasons. Constraint functions are used in the optimization procedure to define the limits of solution space being searched. Limiting the solution space means that the optimum obtained through optimization will satisfy both the fitness function and other requirements. Some possible constraint functions include a maximum monetary cost, a maximum number of injuries and/or fatalities, or a minimum amount of the population protected. Using many or stringent constraint functions can severely limit the solution space, meaning the optimum found may be far from adequate.

The purpose of the predictor functions are to mathematically represent how the societal damage indicators are a function of the hazard, population, and built environment variables. Put succinctly in mathematical form:

$$x = x(n_0, n_1, \dots n_i) \tag{2}$$

where $\boldsymbol{n}$ are hazard, population, and built environment variables. Because the SORD framework utilizes a multi-disciplinary approach, it may be the case that there will be a complicated blend of variables that inform the societal damage indicators. One method of incorporating these variables into a predictor function is use statistical regression analysis. For example, in the case study which follows in Chapter 4, the predictor functions were linear regression models which estimate two societal damage metrics, namely, household dislocation duration and business downtime duration, as functions of building damage state, utility loss, household racial make-up, and other demographic and hazard outcome information.

3.5.1 User Recommendations

The main reason that optimization is used in the SORD framework is because of the vast amounts of possible resource distribution solutions that provide *some* level of societal fairness.

Since the purpose of the framework is to design resource distributions which provide the *best* level of societal fairness, optimization is used to check that vast solution space of possible distributions. Instead of depending on finding derivatives or Hessians of an enormous function describing the effects of a resource distribution on community-wide societal fairness, iterative methods are recommended instead. This leads to the recommended use of heuristics, such as the genetic algorithms used for the Lumberton case study in Chapter 4. Genetic Algorithm optimization, which is based on biological natural selection, takes advantage of stochastic search methods applied on large populations of potential solutions, which means that great amounts of information can be considered, processed, and used at each iteration to approach an optimal solution.

The other decision specific for this framework is the formulation of the fitness function. In the SORD framework, the fitness function should be based on the measure of societal fairness. In the case study in Chapter 4, the fitness function for equity was formulated based on minimizing the average difference in outcomes between members of the population. Other possible fitness functions include minimizing the *range* in outcomes across the community, or squaring the differences to place more emphasis on the larger discrepancies in the community.

The development of predictor functions may prove challenging. For the case study mentioned above, regression analyses were conducted to produce the predictor functions, but also took advantage of being able to correlate recorded societal damages to the explanatory variables. Users of the SORD framework may find useful a review of a collection of existing models that aim to predict certain societal damage indicators located in Chapter 2.

3.6 Decision-Making

The final step of the SORD framework is to evaluate the societally-optimized resource distribution strategy(ies) which were developed. Depending on a combination of conditions, including the community being designed for, the resource types used, and the societal goals of the resource distributions, the resource distribution(s) obtained through optimization may not be ideal. Perfectly fair or optimal distributions will be rare, if not impossible, to obtain due to the inherently complex interactions of a community and its human, built, and natural systems. In some cases, existing disparities within the population may not be possible to overcome with resource distributions alone. It will be up to the user of the framework to decide if the degree of societal fairness achieved through the optimization is sufficient (if the solutions are "fair enough"). If not, different resource types or societal goals may need to be considered until an acceptable solution is found.

Comparative evaluation can be completed if the framework was used multiple times to produce a resource distribution strategy for various combinations of hazards, scopes, and resource types. For example, the user may have been tasked to determine which type of hazard can be most well-addressed by societally-fairly distributing resources, on the basis of overall cost. For that example, and for many other applications, the benefit-cost analysis may be the desired decision-making tool. Noted prior in this chapter was the dependence on available funding that exists when attempting to implement solutions.

3.6.1 User Recommendations

Since importance was placed on being able to quantify each of the factors used in the SORD framework, the benefit-cost analysis is highly applicable as an evaluation and decision-making

tool. For instance, the benefit-cost analysis provides a formal procedure in which the available funding could be used most efficiently. Otherwise, ranking criteria, weighting systems, or any other decision-making procedure may be the preferred tool for the user; the SORD framework is not dependent on a particular decision-making method.

3.7 Summary

The result following this framework will be the development of one or more potential resource management strategies that can be used for a particular hazard scenario affecting a particular community. These strategies will be suited for the population of interest by using locally-relevant information. The scope of the resource management strategy development should be purposely chosen to balance the needs of the community with the capabilities of the user and the quantity and quality of the information available to them. The strategies should be deliberately developed with the purpose of achieving societal fairness amongst the affected population. This purpose is met through designing the strategies using an objective computational optimization procedure, in lieu of subjective or arbitrary methods. Finally, the strategies developed will have undergone a formal decision-making procedure to evaluate their applicability and feasibility.

4. Case Study

A case study on the application of the Societally-Optimized Resource Distribution (SORD) framework is presented in this chapter. The case study described herein used information collected as part of a longitudinal study on community disaster resilience centered in Lumberton, North Carolina. Data regarding household and business characteristics and experiences from before, during and after intense flooding caused by 2016 Hurricane Matthew and subsequent 2018 Hurricane Florence was used. The case study walked through the six steps of the SORD framework, outlined in Chapter 3, with the goal of comparing between several equality- and equity-based resource distribution strategies.

The longitudinal Lumberton study is an ongoing collaborative project conducted by researchers from the National Institute of Standards of Technology (NIST) Center of Excellence for Risk-Based Community Resilience Planning (the Center) and the NIST Engineering Laboratory. The Center itself is an interdisciplinary collaboration headquartered at Colorado State University in Fort Collins, Colorado, currently with researchers from thirteen universities across the United States, including the University of Kansas. The purpose of the Center is to bring together experts in resilience from the fields of engineering, economics, social sciences and data management for the development of system-level community resilience models. Ultimately, all of this work is intended to lead to the development of an Interdependent Networked Community Resilience Modeling Environment (IN-CORE), which will be able to compute resiliency metrics at a community level.

Along this mission, the Lumberton study was initiated to first examine the impacts and recovery of important social units and their interaction, namely residential and education sectors, defined at the housing unit level and divided by school districts in the city, as well as to improve

flood hazard fragility functions and develop models for societal damages and recovery. The overall goals of the study have expanded since the initiation of the project (for example, now with the primary objectives to (1) provide the necessary data for validating hazard, impact, and recovery models for IN-CORE, and (2) advance multi-disciplinary, longitudinal field study metrology). A full report on the initial conditions and the first field study, 'Wave 1', of the longitudinal Lumberton study has also been published as a Special Publication by NIST and is available publicly for interested readers (van de Lindt et al. 2018). Other publications on subsequent *Waves* are steadily becoming available online (e.g., Khajehei 2019; Sutley et al. 2019; Aghababaei et al. 2020; van de Lindt et al. 2020; Watson et al. 2020).

This case study parallels some of the objectives of the Center's study. First, several societal damage indicators, for the purpose of examining societal damage and recovery within the context of Lumberton in 2016, were investigated using correlation analyses of the household and business data collected by the Center. Second, models for predicting societal damages to households and businesses were developed through a regression analysis. Third, these models were used to conduct optimizations on resource distribution strategies on the bases of different types of societal fairness. The results of the optimizations were finally compared using a benefit-cost analysis.

4.1 Hazard Type and Intensity

Under the SORD framework, the resulting resource distribution strategies are meant to be applicable to particular hazard types and intensities. The case study was based on the events surrounding Lumberton, NC, in 2016 during and after Hurricane Matthew. Therefore, an inland riverine flooding hazard type was chosen for the case study, as this type of flooding was what actually occurred. Along this same line, the hazard intensity was chosen to be a 'Matthew-level event', or in other words, riverine flooding due to conditions mirroring those of Hurricane Matthew

in North Carolina. Choosing this particular hazard intensity was necessary as the data used in the later stages of the case study is only valid for said hazard and intensity.

Some context to the community, the hurricane and the subsequent flooding is provided here, synthesized from van de Lindt et al. (2018). Matthew was a major hurricane which formed on September 28, 2016, and quickly intensified to a Category 5 level (on the Saffir-Simpson scale) on October 1, 2016, with highest 1-minute sustained wind speeds recorded at 270 km/h (165 mph). Matthew had made landfall multiple times, including over Haiti, Cuba and the Bahamas, before reaching the southeastern coast of the United States, somewhat weakened, as a Category 3 storm. The hurricane followed this coast north for approximately four days, making its final landfall as a Category 1 storm just north of Charleston, South Carolina, before eventually dissipating as the storm moved eastward into the Atlantic Ocean.

The City of Lumberton, NC, is the county seat of Robeson County, and is situated along the banks of the Lumber River. While the majority of Lumberton, the portion north of the Lumber, resides at a higher elevation, the southern portion of the city sits only slightly above the elevation of the river. This southern portion has been protected by a 2.8 mile long levee system since 1974. However, despite the protective efforts made in the city, heavy rainfall just prior to and during Hurricane Matthew resulted in historic flooding in the city on and beyond October 3, 2016. The National Water Information System, operated by the United State Geological Survey (2020), showed that the peak gage height of the Lumber River at Lumberton was nearly 22 ft (6.7 m; Figure 2), much greater than the National Weather Service (NWS) flood stage of 13 ft (4.0 m). The NWS defines “flood stage” as the gage height at which a hazard becomes present to the surrounding community. Note in Figure 2 a second peak gage height corresponding to 2018 Hurricane Florence, wherein a second intense flooding scenario occurred just two years later.

While similarities exist between the flooding due to Hurricanes Matthew and Florence, this case study is focused on the conditions and outcomes from the former.

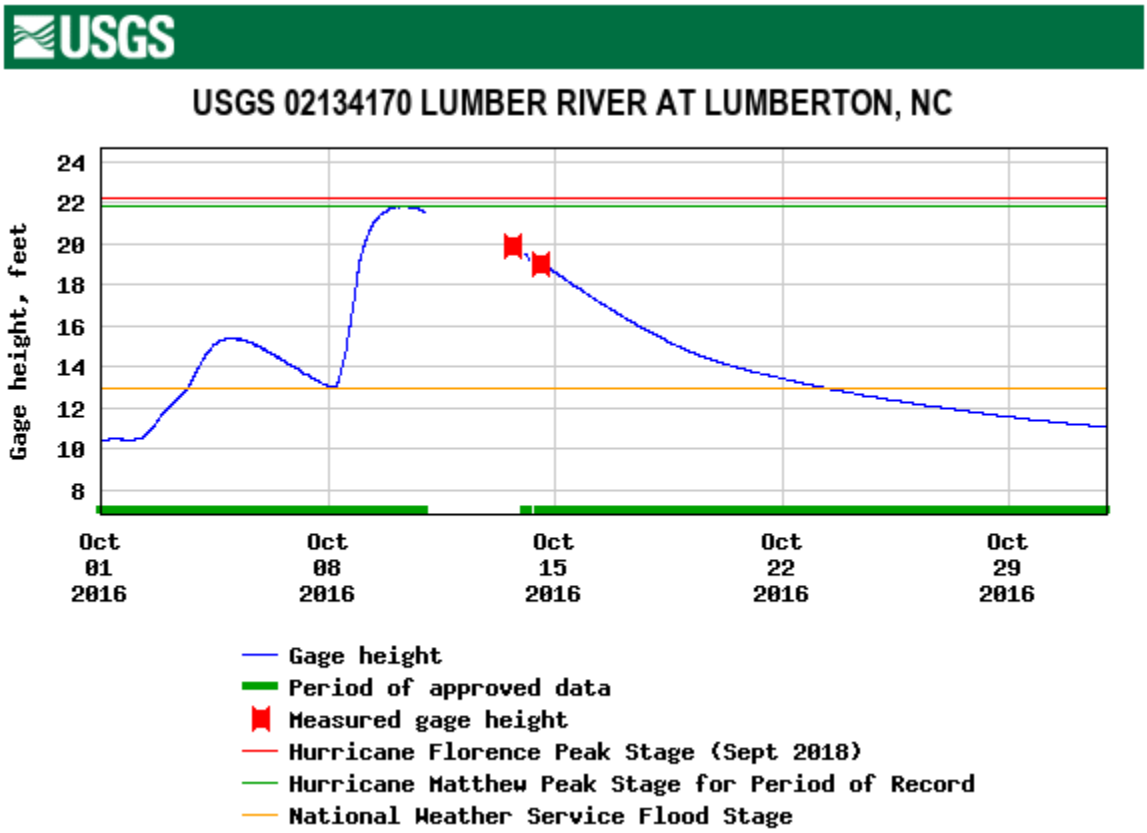

Figure 2. Gage height readings of the Lumber River at Lumberton, NC, due to 2016 Hurricane Matthew (USGS 2020).

A great deal of the resulting flood damages to Lumberton may be attributed to a gap in the levee system. An underpass existed at the intersection of a railroad and Interstate 95 on the northwestern portion of the levee system. A Flood Insurance Study for Robeson County, NC, conducted by FEMA and the State of North Carolina in 2005, purports that this opening would have been blocked by the City of Lumberton using sandbags when a flood was imminent (FEMA 2005). However, a subsequent Flood Insurance Study published in 2014, describes this plan to not be in accordance to FEMA's regulations regarding structure closures of levee openings (FEMA

2014a). Despite these reports, no retrofits were applied to the overpass before Hurricane Matthew arrived, and the plan to use sandbags was not followed through in 2016. Even further, CSX railroad prevented citizens from piling sandbags into the levee breech in the days leading up to 2018 Hurricane Florence (Fain 2018, McCausland 2018). While sandbags alone probably would not have completely prevented flooding, the unfortunate results of no action were estimated damages of over $200 million, corresponding to the 2016 flood event with a return period of between 500 and 1000 years (NCEM 2018).

4.2 Societal Damage Indicators

The second step of applying the SORD framework to the case study was to choose the societal damage indicators and metrics. Given the type and amount of data made available through the work of the Center, there was potential to adopt both pre-event and post-event indicators. Pre-event indicators consist of the existing conditions and characteristics of the community, most notably population and organization demographics, as well as available resources and existing disaster mitigation measures. The most obvious post-event indicators are recorded physical and/or societal damages, which can also be supplemented with other indicators such as shifts in overall community demographics or rates of community recovery.

The population of Lumberton was found to be highly diverse and minority-majority, the latter meaning that less than 50% (38.4%) of the estimated total population of 21,646 identified as non-Hispanic White in the year Hurricane Matthew occurred (USCB 2016). Additionally, the American Community Survey found that a substantial portion of the population (35.1%) was below the federal poverty level, a percentage that was far greater than the national average at the time (15.1%). As noted in Chapter 2, researchers showed that minority groups were affected by

and recovered from natural hazards disproportionately. Similarly to race and ethnicity, previous studies have also shown disproportionate impacts on financially-disadvantaged populations.

The inventory of potential societal damage indicators was defined by the data collected by the Center in Lumberton, which in turn was prescribed by the survey tools used by its investigators. The data from three surveys were used for this case study: 1) Household Wave 1 survey (Peacock et al. 2020) conducted November 2016, 2) Household Wave 2 survey (Sutley et al. 2020) and 3) Business Wave 2 survey (Xiao et al. 2020), both conducted January 2018. In the context of the Center's longitudinal Lumberton study, the Wave 1 survey was administered to 567 housing units shortly after the floodwaters in Lumberton dissipated, and the Wave 2 surveys were administered approximately one year later to the same housing units and an additional sample set of businesses to document recovery progress. 350 businesses were identified as the original sample set through the online business database *ReferenceUSA*™; the business sample set was reduced to 217 after accounting for outdated and incorrect data (e.g., closed businesses, duplicate data). The housing sample used a two-stage stratified random cluster sample. To maximize efficiency in the field, housing units located in the floodplain and predicted inundation zone were drawn at a ratio of three-to-one relative to housing units located outside of the floodplain and predicted inundation zone. As such, after data collection, survey responses in the latter category were triplicated to accommodate the three-to-one sampling design, and match the proportioning of the actual city. The resulting survey sample, deemed statistically representative of the Lumberton, NC, community, was 861 households and 217 businesses.

In the end, not all of the data collected through the Center's surveys would be used through the entire case study. Primarily, the survey data provided by the Center was too granular for use in the case study for two reasons. First, the level of detail the data was collected at meant there were

many relatable variables that, if used individually, would cause the analysis to be overwhelmingly elaborate. Second, two sets of household data were collected at different times (from Wave 1 and Wave 2). The data from the two points in time needed to be resolved into a single set of time-independent data, due to the limitation of the current SORD framework not considering recovery as a function of time. Therefore, new variables were established for use in this case study; each of the new variables encompassed one or more of the original variables. The criteria for encompassing multiple original variables under one new variable include the following:

i) Broadening the variable to reflect multiple, similar pieces of information. For example, a new variable for a household's maximum duration of loss of utilities in days was created by compiling the individual durations of utility loss for many different utility types (e.g., water, electricity, natural gas).
ii) Broadening the variable to reflect multiple surveys. For example, a new household variable describing the highest level of education attained by a resident considered the associated responses from the household surveys for both Wave 1 and Wave 2 of the longitudinal study, and used the more recent data where available.

Once the new variables were established. the next step was to categorize potential social damage indicators. The initial list of societal damage indicators tested in this case study are shown below in Tables 1 through 4; Tables 1 and 3 present the pre-event indicators for households and businesses, respectively, while Tables 2 and 4 present the post-event indicators for the same, respectively. The complete list of the compiled variables, their definitions, rules and original variables used for compiling, and the type of each variable is provided in Appendix A, Tables A1 and A2.

Table 1. Household pre-event societal damage indicators.

Category	Indicator description
Home building properties	• Building floor area • Building construction material • Building foundation type • Building quality • Building occupancy type • Building stories
Socioeconomic demographics	• Highest level of education completed • Presence of seniors in the household • Presence of minors in households • Full-time employment in the household • Ownership of household's home • Household annual income • Household racial and ethnic makeup
Hardship preparedness funding	• Household's home insurance

Table 2. Household post-event societal damage indicators.

Category	Indicator description
Damage to home or household	• Floodwater height at building • Damage state of interior of home • Damage state of overall building • Days of utility loss • Days of work missed
Repair and recovery funding	• Insurance disbursement received • Delay of insurance disbursement • Amount of repairs covered by insurance • Applied for non-insurance external funding • External funding support received • Delay in receiving external funding • Amount of repairs covered by insurance and external funding
Recovery factors and progress	• Household dislocation • Household's physical access to the community • Effect of funding delay on household dislocation • Effect of workplace conditions on dislocation duration • Effect of school conditions on dislocation duration • Effect of business closures on dislocation duration • Days taken to fully repair home

Table 3. Business pre-event societal damage indicators.

Category	Indicator description
Business properties	• Business size based on Small Business Administration standards (SBA 2019) • Duration business can operate at a deficit • Dependency of the business on location • Ownership structure of the business • Ownership of the business's building
Owner or manager demographics	• Age of the owner or manager interviewed • Racial and ethnic makeup of the owner or manager • Highest level of education completed • Gender of the owner or manager
Hardship preparedness funding	• Business covered by any type of insurance
Business profitability and capacity	• Number of employees pre-disaster • Profitability of the business pre-disaster

Table 4. Business post-event societal damage indicators.

Category	Indicator description
Damage to business or building	• Floodwater height at building • Damage state of overall building • Damage state of equipment and/or machinery • Damage state of inventory and contents • Days of utility loss • Customer loss experienced by business • Employees experienced difficulties due to transportation issues • Employees experienced difficulties due to personal damages • Employees experienced difficulties due to school conditions • Employees experienced difficulties due to physical injury • Employees experienced difficulties due to mental injury
Repair and recovery funding	• Insurance disbursement received • Delay of insurance disbursement • Applied for non-insurance external funding • External funding support received • Delay in receiving external funding
Recovery factors and progress	• Business downtime • Operational capacity of business at time of survey • Locality/location of customers post-disaster • Locality/location of suppliers post-disaster • Number of employees post-disaster • Profitability of the business post-disaster • Status of recovery at time of survey

Based on the definition of resilience, the effects of resource distribution on the resilience of a community exposed to flood hazards should be measured by observing changes in the community's robustness, resourcefulness, rapidity of recovery, or system redundancies (recall the four R's of resilience, as defined by Bruneau et al. 2003). The rapidity of recovery was deemed most appropriate for this case study. This was not only because recovery could be represented easily by some of the societal damage indicators listed above, but also because recovery was shown in Chapter 2 to be influenced by many socio-demographic factors. Since the goal of the framework

is to use societal optimization, it naturally follows that socio-demographic factors should be adequately included in the analysis.

Amongst the post-event societal damage indicators, two societal indicators appeared to be ideal for representing the state of the community after a flooding event. For households, household dislocation was chosen, with household dislocation duration as the corresponding measure; first, this measure is both quantitative and continuous, and second, it is representative of disaster recovery and has been shown to be a function of both physical damages and numerous socio-economic household demographics. For businesses, the business downtime indicator and business downtime duration measure was chosen for the same reasons.

Several societal damage indicators use the term *damage state*. Damage states describe the level of damage experienced by the subject (in this case, a building or parts thereof), and were determined by the Center's researchers at the time of their field studies in Lumberton through visual inspections. The criteria for each damage state for each subject was developed by the Center's researchers for the longitudinal Lumberton study, and are included in Appendix B.

Two types of statistical analyses were conducted to reduce the number of potential societal damage: 1) a correlation analysis to investigate the interactions between the socio-economic demographic household factors, and 2) a regression analysis to determine which societal damage indicators are the most statistically significant.

4.2.1 Correlation Analysis

A correlation analysis was conducted on the household socio-demographic factors. The purpose of this correlation analysis was to investigate the intersectionality between the different demographic factors. Based on these intersectionalities, it could also be possible to define social

vulnerability to floods using composite variables (Tapsell et al. 2002, Cutter et al. 2003). Using composite variables could reduce the number of societal damage indicators necessary to adequately represent the community in question when using the SORD framework. Typically, reducing this number means that a lesser amount of data would need to be collected when developing the community portfolio, or step 3 of the SORD framework. However, for this case study, it was known from the beginning the amount and types of data that was already collected by the Center in Lumberton, so the primary goal of this correlation analysis was to observe the intersectionalities between some societal damage indicators.

The societal damage indicators listed below in Table 5. In order to perform the correlation analysis, the factors were placed into three categories which would be compared to one-another.

Table 5. Social vulnerability factors identified for correlation analysis.

Category	**Factor**
Occupancy	• Household occupies a single- or multi-family building • Household size • Children in household • Housing tenure status • Mortgage status • Highest education level in household
Race and Ethnicity	• Household is White, Black, American Indian, Hispanic, and/or minority
Annual Income	• Household has an annual income above or below a cutoff level

In this analysis, a household was considered a particular race if they did not identify as more than one race. A household was considered to be a “minority” household if they identified as Hispanic and/or not White. Additionally, annual income cutoffs were used in lieu of the households’ actual annual incomes. This was done such that a population of households could be divided at a certain income cutoff level, where the households with annual incomes below the cutoff would have significantly higher social vulnerability. Therefore, the purpose of the income

cutoff is similar in principle to the Federal Poverty Level published by the U.S. Department of Health and Human Services.

Both of the Wave 1 and Wave 2 household survey data were used to calculate the correlations in this analysis. However, these datasets were kept separate, which was not the case for the rest of this case study. The purpose of keeping the Wave 1 and Wave 2 data separate was to observe the changes that may occur in the intersectionalities between social vulnerability factors over time after a disaster.

The correlation analysis was conducted using bivariate Pearson correlations. Pearson correlation coefficients range between -1 and 1 for total negative and total positive correlations, respectively. Strong Pearson correlations implies that when comparing two variables, their datapoints rest closer to a linear "line-of-best-fit". A positive correlation means that this line has a positive slope, and vice versa for negative correlations. Note that the magnitude of the correlation coefficient does not provide any information about the magnitude of the slope itself (e.g., a correlation coefficient of 1 does not imply that the slope of the line-of-best-fit is equal to 1).

Mathematically, the Pearson correlation coefficient of two variables is equal to the covariance between the two variables divided by the product of each variable's standard deviation. For this analysis, the correlations were determined using the bivariate correlations function in the *IBM SPSS Statistics 26* (*SPSS*) program.

Tables 6 through 11 present the bivariate correlations obtained in this analysis. Tables 6 through 8 present the Wave 1 correlations between the Occupancy social vulnerability factors versus Race and Ethnicity factors (Table 6), the Income versus Race and Ethnicity factors (Table 7), and the Income versus Occupancy factors (Table 8). Tables 9 through 11 present the same but

for the Wave 2 household survey data that was collected approximately one year later. Correlation coefficients are shown along with the statistical significance of each coefficient, ‘Sig. (2-tailed)’, and the number of datapoints used to calculate each coefficient, ‘N’. The correlations deemed significant at the 0.01 level on a two-tailed test are highlighted in bold.

Table 6. Correlations between Occupancy and Race and Ethnicity social vulnerability factors in Wave 1.

		Multi-Family	Household Size	Children in HH	Renter	Mortgage	Years of Education
Multi-Family Building	Correlation	1.00	0.01	**.117***	**.630****	-0.10	**-.178****
	Sig. (2-tailed)		0.91	**0.05**	**0.00**	0.16	**0.00**
	N	829	282	282	288	191	265
Household Size	Correlation	0.01	1.00	**.661****	0.11	**.200****	0.10
	Sig. (2-tailed)	0.91		**0.00**	0.07	**0.00**	0.11
	N	282	295	295	291	198	278
Children in Household	Correlation	**.117***	**.661****	1.00	**.255****	**.323****	0.11
	Sig. (2-tailed)	**0.05**	**0.00**		**0.00**	**0.00**	0.06
	N	282	295	295	291	198	278
Renter Tenure Status	Correlation	**.630****	0.11	**.255****	1.00	.c	**-.309****
	Sig. (2-tailed)	**0.00**	0.07	**0.00**		0.00	**0.00**
	N	288	291	291	304	200	276
Has a Mortgage	Correlation	-0.10	**.200****	**.323****	.c	1.00	0.01
	Sig. (2-tailed)	0.16	**0.00**	**0.00**	0.00		0.87
	N	191	198	198	200	201	189
Years of Education	Correlation	**-.178****	0.10	0.11	**-.309****	0.01	1.00
	Sig. (2-tailed)	**0.00**	0.11	0.06	**0.00**	0.87	
	N	265	278	278	276	189	278
High School Diploma or Less	Correlation	**.170****	**-.132***	**-.159***	**.330****	0.02	**-.722****
	Sig. (2-tailed)	**0.01**	**0.04**	**0.01**	**0.00**	0.78	**0.00**
	N	237	250	250	248	180	247
Black Household	Correlation	0.08	-0.02	-0.05	**.245****	-0.10	**-.156****
	Sig. (2-tailed)	0.16	0.75	0.40	**0.00**	0.17	**0.01**
	N	280	293	293	290	198	278
American Indian Household	Correlation	-0.08	0.09	**.142***	-0.02	0.04	-0.11
	Sig. (2-tailed)	0.17	0.15	**0.02**	0.71	0.56	0.07
	N	273	283	283	280	194	268
Hispanic Household	Correlation	**.249****	**.228****	**.270****	**.123***	0.10	0.01
	Sig. (2-tailed)	**0.00**	**0.00**	**0.00**	**0.04**	0.14	0.85
	N	280	293	293	293	201	277
Household is Hispanic and/or not White	Correlation	0.10	**.160****	**.172****	**.282****	-0.04	**-.213****
	Sig. (2-tailed)	0.11	**0.01**	**0.00**	**0.00**	0.58	**0.00**
	N	280	293	293	290	198	278

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Cannot be computed because at least one of the variables is constant.

Table 7. Correlations between Income and Race and Ethnicity social vulnerability factors in Wave 1.

		Black	American Indian	Hispanic	Hispanic and/or not White
Income Less than $4,000/yr	Correlation	**.174****	-0.07	0.11	0.08
	Sig. (2-tailed)	**0.00**	0.26	0.08	0.18
	N	259	249	258	259
Income Less than $6,000/yr	Correlation	**.224****	-0.11	0.07	**.127***
	Sig. (2-tailed)	**0.00**	0.09	0.26	**0.04**
	N	259	249	258	259
Income Less than $8,000/yr	Correlation	**.122***	0.10	0.02	**.166****
	Sig. (2-tailed)	**0.05**	0.11	0.69	**0.01**
	N	259	249	258	259
Income Less than $10,000/yr	Correlation	**.173****	0.08	0.01	**.198****
	Sig. (2-tailed)	**0.01**	0.19	0.88	**0.00**
	N	259	249	258	259
Income Less than $12,000/yr	Correlation	**.123***	0.10	0.12	**.213****
	Sig. (2-tailed)	**0.05**	0.11	0.05	**0.00**
	N	259	249	258	259
Income Less than $15,000/yr	Correlation	**.166****	0.11	0.08	**.266****
	Sig. (2-tailed)	**0.01**	0.08	0.19	**0.00**
	N	259	249	258	259
Income Less than $20,000/yr	Correlation	**.209****	0.08	0.05	**.287****
	Sig. (2-tailed)	**0.00**	0.19	0.43	**0.00**
	N	259	249	258	259
Income Less than $25,000/yr	Correlation	**.224****	0.07	0.02	**.276****
	Sig. (2-tailed)	**0.00**	0.27	0.78	**0.00**
	N	259	249	258	259
Income Less than $30,000/yr	Correlation	**.166****	0.05	0.02	**.194****
	Sig. (2-tailed)	**0.01**	0.47	0.77	**0.00**
	N	259	249	258	259
Income Less than $40,000/yr	Correlation	**.140***	-0.03	-0.02	0.12
	Sig. (2-tailed)	**0.02**	0.64	0.71	0.05
	N	259	249	258	259
Income Less than $50,000/yr	Correlation	**.197****	-0.01	-0.06	**.173****
	Sig. (2-tailed)	**0.00**	0.82	0.35	**0.01**
	N	259	249	258	259

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 8. Correlations between Income and Occupancy social vulnerability factors in Wave 1.

		Multi-Family	Household Size	Children in HH	Renter	Mortgage	Years of Education
Income Less than $4,000/yr	Correlation	**.179****	-0.07	0.07	**.152***	0.06	-0.08
	Sig. (2-tailed)	**0.00**	0.28	0.29	**0.01**	0.43	0.20
	N	246	259	259	258	174	253
Income Less than $6,000/yr	Correlation	**.247****	-0.01	0.07	**.279****	0.06	-0.09
	Sig. (2-tailed)	**0.00**	0.86	0.24	**0.00**	0.43	0.14
	N	246	259	259	258	174	253
Income Less than $8,000/yr	Correlation	**.147***	-0.10	-0.02	**.232****	-0.09	**-.245****
	Sig. (2-tailed)	**0.02**	0.10	0.74	**0.00**	0.25	**0.00**
	N	246	259	259	258	174	253
Income Less than $10,000/yr	Correlation	**.183****	**-.147***	-0.03	**.277****	-0.11	**-.306****
	Sig. (2-tailed)	**0.00**	**0.02**	0.66	**0.00**	0.13	**0.00**
	N	246	259	259	258	174	253
Income Less than $12,000/yr	Correlation	**.246****	**-.159***	0.01	**.331****	-0.12	**-.312****
	Sig. (2-tailed)	**0.00**	**0.01**	0.93	**0.00**	0.11	**0.00**
	N	246	259	259	258	174	253
Income Less than $15,000/yr	Correlation	**.249****	**-.144***	0.00	**.399****	**-.168***	**-.390****
	Sig. (2-tailed)	**0.00**	**0.02**	0.98	**0.00**	**0.03**	**0.00**
	N	246	259	259	258	174	253
Income Less than $20,000/yr	Correlation	**.169****	**-.122***	0.01	**.401****	-0.12	**-.374****
	Sig. (2-tailed)	**0.01**	**0.05**	0.87	**0.00**	0.13	**0.00**
	N	246	259	259	258	174	253
Income Less than $25,000/yr	Correlation	**.179****	-0.06	-0.02	**.434****	**-.150***	**-.404****
	Sig. (2-tailed)	**0.00**	0.34	0.71	**0.00**	**0.05**	**0.00**
	N	246	259	259	258	174	253
Income Less than $30,000/yr	Correlation	**.286****	-0.11	-0.08	**.484****	-0.11	**-.471****
	Sig. (2-tailed)	**0.00**	0.07	0.19	**0.00**	0.16	**0.00**
	N	246	259	259	258	174	253
Income Less than $40,000/yr	Correlation	**.201****	**-.163****	**-.170****	**.395****	-0.11	**-.543****
	Sig. (2-tailed)	**0.00**	**0.01**	**0.01**	**0.00**	0.15	**0.00**
	N	246	259	259	258	174	253
Income Less than $50,000/yr	Correlation	**.141***	**-.180****	**-.156***	**.364****	**-.179***	**-.498****
	Sig. (2-tailed)	**0.03**	**0.00**	**0.01**	**0.00**	**0.02**	**0.00**
	N	246	259	259	258	174	253

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Factors which are significantly correlated with many other vulnerability factors are ideal candidates for forming composite factors. In other words, composite factors need vulnerability factors which can "explain" other vulnerability factors. An example is the "presence of minors in the household" factor, which was significantly correlated with most of the other Occupancy category factors in Wave 1. The exception was "number of years of education", though having children in the household was negatively correlated with having a high school education or less. In fact, as can be seen in Table 6, all Occupancy-type factors were significantly correlated with having a high school education or less, except for the mortgage factor.

Comparing the Race and Ethnicity factors with the Occupancy factors showed that being either a Hispanic household or a Minority household was correlated to the highest number of Occupancy factors. In contrast, the only Occupancy factor to not be significantly correlated with a Race or Ethnicity factor was having a mortgage.

Table 7 presented the correlations between income cutoffs and Race and Ethnicity factors. The Black and Minority household factors were correlated to nearly every income cutoff considered, with the opposite being the case for the American Indian and Hispanic household factors. For the purposes of identifying potential income cutoffs in Wave 1, the $20,000/yr and $25,000/yr cutoffs were observed to having relatively high magnitude correlation coefficients.

Three of the six Occupancy social vulnerability factors (household size, presence of minors in the household, and having a mortgage) did not have any significant, positive correlations with any of the income cutoffs. Of particular note, having children in the household was not significantly correlated with any income cutoff until the $40,000/yr point. Significant and positive correlations were observed for all of the low-income cutoffs when compared to living in multi-family buildings and being renters, which was an expected result.

For the Wave 1 data, which was collected one month after the 2016 flooding in Lumberton, NC, $20,000/yr appears to be suitable annual household income cutoff. This income cutoff had significant correlations with many factors in both the Race and Ethnicity category and Occupancy category. Other possible cutoffs included $15,000/yr, $40,000/yr, and $50,000/yr due to them having strong and significant correlations with Occupancy social vulnerability factors, though not necessarily with the Race and Ethnicity factors.

Table 9. Correlations between Occupancy and Race and Ethnicity social vulnerability factors in Wave 2.

		Multi-Family	Household Size	Children in HH	Renter	Mortgage	Years of Education
Multi-Family Building	Correlation	1.00	**-.193****	0.03	**.748****	.c	**-.254****
	Sig. (2-tailed)		**0.00**	0.56	**0.00**	0.00	**0.00**
	N	860	369	368	297	219	345
Household Size	Correlation	**-.193****	1.00	**.684****	-0.08	**.219****	**.202****
	Sig. (2-tailed)	**0.00**		**0.00**	0.15	**0.00**	**0.00**
	N	369	369	368	297	219	341
Children in Household	Correlation	0.03	**.684****	1.00	0.05	**.318****	**.134***
	Sig. (2-tailed)	0.56	**0.00**		0.37	**0.00**	**0.01**
	N	368	368	368	297	219	340
Renter Tenure Status	Correlation	**.748****	-0.08	0.05	1.00	0.05	**-.293****
	Sig. (2-tailed)	**0.00**	0.15	0.37		0.51	**0.00**
	N	297	297	297	297	219	293
Has a Mortgage	Correlation	.c	**.219****	**.318****	0.05	1.00	0.10
	Sig. (2-tailed)	0.00	**0.00**	**0.00**	0.51		0.13
	N	219	219	219	219	219	219
Years of Education	Correlation	**-.254****	**.202****	**.134***	**-.293****	0.10	1.00
	Sig. (2-tailed)	**0.00**	**0.00**	**0.01**	**0.00**	0.13	
	N	345	341	340	293	219	345
High School Diploma or Less	Correlation	**.243****	**-.198****	**-.175****	**.248****	-0.09	**-.755****
	Sig. (2-tailed)	**0.00**	**0.00**	**0.00**	**0.00**	0.18	**0.00**
	N	345	341	340	293	219	345
Black Household	Correlation	0.08	0.00	-0.08	**.215****	**-.244****	**-.220****
	Sig. (2-tailed)	0.13	0.96	0.16	**0.00**	**0.00**	**0.00**
	N	349	345	344	297	219	345
American Indian Household	Correlation	**.147****	**-.126***	-0.09	0.05	0.06	-0.09
	Sig. (2-tailed)	**0.01**	**0.02**	0.08	0.37	0.37	0.11
	N	349	345	344	297	219	345
Hispanic Household	Correlation	0.07	-0.06	0.00	**.204****	-0.03	-0.02
	Sig. (2-tailed)	0.19	0.23	0.96	**0.00**	0.62	0.68
	N	349	345	344	297	219	345
Household is Hispanic and/or not White	Correlation	**.235****	0.00	-0.06	**.280****	-0.12	**-.271****
	Sig. (2-tailed)	**0.00**	0.95	0.25	**0.00**	0.08	**0.00**
	N	349	345	344	297	219	345

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Cannot be computed because at least one of the variables is constant.

Table 10. Correlations between Income and Race and Ethnicity social vulnerability factors in Wave 2.

		Black	Native American	Hispanic	Hispanic and/or not White
Income Less than $4,000/yr	Correlation	**.227****	0.02	-0.06	**.203****
	Sig. (2-tailed)	**0.00**	0.74	0.29	**0.00**
	N	345	345	345	345
Income Less than $6,000/yr	Correlation	**.205****	0.07	-0.07	**.275****
	Sig. (2-tailed)	**0.00**	0.17	0.18	**0.00**
	N	345	345	345	345
Income Less than $8,000/yr	Correlation	**.253****	**.106***	0.04	**.324****
	Sig. (2-tailed)	**0.00**	**0.05**	0.41	**0.00**
	N	345	345	345	345
Income Less than $10,000/yr	Correlation	**.228****	0.07	0.01	**.318****
	Sig. (2-tailed)	**0.00**	0.18	0.91	**0.00**
	N	345	345	345	345
Income Less than $12,000/yr	Correlation	**.265****	0.04	-0.01	**.334****
	Sig. (2-tailed)	**0.00**	0.42	0.89	**0.00**
	N	345	345	345	345
Income Less than $15,000/yr	Correlation	**.226****	0.08	0.03	**.322****
	Sig. (2-tailed)	**0.00**	0.12	0.54	**0.00**
	N	345	345	345	345
Income Less than $20,000/yr	Correlation	**.230****	**.110***	0.01	**.332****
	Sig. (2-tailed)	**0.00**	**0.04**	0.87	**0.00**
	N	345	345	345	345
Income Less than $25,000/yr	Correlation	**.192****	0.07	0.01	**.249****
	Sig. (2-tailed)	**0.00**	0.22	0.86	**0.00**
	N	345	345	345	345
Income Less than $30,000/yr	Correlation	**.199****	0.04	0.03	**.271****
	Sig. (2-tailed)	**0.00**	0.48	0.63	**0.00**
	N	345	345	345	345
Income Less than $40,000/yr	Correlation	**.162****	0.06	0.00	**.262****
	Sig. (2-tailed)	**0.00**	0.27	0.99	**0.00**
	N	345	345	345	345
Income Less than $50,000/yr	Correlation	**.171****	0.09	-0.01	**.276****
	Sig. (2-tailed)	**0.00**	0.11	0.81	**0.00**
	N	345	345	345	345

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 11. Correlations between Income and Occupancy social vulnerability factors in Wave 2.

		Multi-Family	Household Size	Children in HH	Renter	Mortgage	Years of Education
Income Less than $4,000/yr	Correlation	**.236****	-0.09	0.01	**.275****	0.10	**-.107***
	Sig. (2-tailed)	**0.00**	0.10	0.90	**0.00**	0.14	**0.05**
	N	345	341	340	293	219	345
Income Less than $6,000/yr	Correlation	**.280****	0.00	**.109***	**.339****	0.13	**-.187****
	Sig. (2-tailed)	**0.00**	0.97	**0.04**	**0.00**	0.06	**0.00**
	N	345	341	340	293	219	345
Income Less than $8,000/yr	Correlation	**.384****	-0.01	0.06	**.440****	0.13	**-.196****
	Sig. (2-tailed)	**0.00**	0.91	0.29	**0.00**	0.06	**0.00**
	N	345	341	340	293	219	345
Income Less than $10,000/yr	Correlation	**.518****	-0.10	0.02	**.525****	0.03	**-.357****
	Sig. (2-tailed)	**0.00**	0.07	0.70	**0.00**	0.64	**0.00**
	N	345	341	340	293	219	345
Income Less than $12,000/yr	Correlation	**.501****	**-.121***	0.02	**.508****	-0.02	**-.370****
	Sig. (2-tailed)	**0.00**	**0.03**	0.71	**0.00**	0.82	**0.00**
	N	345	341	340	293	219	345
Income Less than $15,000/yr	Correlation	**.523****	**-.206****	-0.03	**.509****	-0.08	**-.409****
	Sig. (2-tailed)	**0.00**	**0.00**	0.63	**0.00**	0.25	**0.00**
	N	345	341	340	293	219	345
Income Less than $20,000/yr	Correlation	**.545****	**-.209****	-0.02	**.537****	**-.150***	**-.434****
	Sig. (2-tailed)	**0.00**	**0.00**	0.71	**0.00**	**0.03**	**0.00**
	N	345	341	340	293	219	345
Income Less than $25,000/yr	Correlation	**.458****	**-.215****	-0.02	**.418****	**-.154***	**-.425****
	Sig. (2-tailed)	**0.00**	**0.00**	0.76	**0.00**	**0.02**	**0.00**
	N	345	341	340	293	219	345
Income Less than $30,000/yr	Correlation	**.424****	**-.171****	-0.02	**.387****	-0.10	**-.424****
	Sig. (2-tailed)	**0.00**	**0.00**	0.67	**0.00**	0.13	**0.00**
	N	345	341	340	293	219	345
Income Less than $40,000/yr	Correlation	**.427****	**-.151****	-0.07	**.385****	**-.155***	**-.426****
	Sig. (2-tailed)	**0.00**	**0.01**	0.20	**0.00**	**0.02**	**0.00**
	N	345	341	340	293	219	345
Income Less than $50,000/yr	Correlation	**.398****	**-.141****	-0.04	**.357****	**-.157***	**-.453****
	Sig. (2-tailed)	**0.00**	**0.01**	0.48	**0.00**	**0.02**	**0.00**
	N	345	341	340	293	219	345

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

The same comparisons as above were made for the Wave 2 data, with the addition of observing changes in correlations over the course of one year by comparing between Wave 1 and Wave 2. Table 9 shows the first set of comparisons made between Occupancy factors and Race and Ethnicity factors for Wave 2. Many of these correlations changed considerably from Wave 1; for example, the presence of minors in the household was no longer correlated with the same number of factors as before. Additionally, in Wave 2, household size and years of education became significantly correlated with many other Occupancy-type factors, the sole exceptions being renter tenure status and having a mortgage, respectively. Race and Ethnicity social vulnerability factors also became less significantly correlated with the Occupancy factors after one year. Previously in Wave 1, the Hispanic and Minority households were significantly correlated with most of the Occupancy factors; this was no longer the case in Wave 2

The correlations between Income factors and Race and Ethnicity factors were fairly similar during Wave 1 and Wave 2. In general, the strength of the correlations between the income cutoffs and the Black and Minority households increased in Wave 2, especially for the lower cutoffs (below $20,000/yr). This suggests that the annual household incomes of Black and Minority households in Lumberton, NC, had stronger linear relationships to lower income cutoffs one year after the 2016 floods. The implication was, therefore, that Black and Minority households did not recover economically, but rather diminished over a 13-month period. The appearance of a pair of positive and significant correlations between American Indian households and certain income cutoffs, which did not exist in the Wave 1 data, may also suggest the same for those households (albeit not as convincingly).

Looking across all the calculated correlations between Race and Ethnicity factors and income cutoffs, the $8,000/yr and $20,000/yr cutoffs each had the largest number of significant correlations, though the $12,000/yr cutoff was also noted due to its relative strength of correlations.

Finally, the income cutoffs were compared to the Occupancy social vulnerability factors for Wave 2. Large changes in the strengths and significances of correlation coefficients were generally observed for all Occupancy factors. Of particular note are the correlations for the "living in multi-family buildings" and "renter" factors versus the income cutoffs, which increased in strength considerably, and more than doubled in strength many cases. As was the case with the previous observations made between Black and Minority households versus income cutoffs, it appears that a greater number of households with low annual income inhabited multi-family buildings and became renters between Wave 1 (November 2016) and Wave 2 (January 2018).

The most appropriate income cutoff for Wave 2 is likely $20,000/yr, the same as for Wave 1. This income cutoff still had a larger number of significant and strong correlations to the factors in both the Occupancy category and the Race and Ethnicity category, compared to the other income cutoffs considered.

The results of this correlation analysis show that the intersectionalities between some social vulnerability factors will change over time. The conclusions made using the Wave 2 income cutoffs suggested that these intersectionalities between social vulnerability factors became stronger over time. Critically, Black and Minority households became more statistically associated with lower income cutoffs after one year of "recovery". The same was seen for renter households, and for those living in multi-family buildings, which implies that, over time, many poorer households lost the ability to live in owner-occupied and/or single-family dwellings.

It happens that the correlation analysis alone was not effective in reducing the number of societal damage indicators to be used in this case study. The first reason for this was noted earlier; the data for all of the societal damage indicators had already been gathered by the Center, so it was not a question of reducing the amount of information needed. Second, the statistics between the societal damage indicators and the chosen resilience metrics (household dislocation duration and business downtime duration) were not considered here. Therefore, it would have been difficult to evaluate the validity of using composite social vulnerability factors in the context of dislocation or downtime duration. Instead of evaluating societal damage indicators against the metrics of resilience in the correlation analysis, it was done in a regression analysis. Using regression analysis provides an additional benefit being able to quantitatively estimate dislocation and downtime durations, rather than only qualitatively gauging them to the other societal damage indicators.

4.2.2 Regression Analysis

A regression analysis was conducted on the identified societal damage indicators. This analysis was performed for the purpose of quantitively relating the corresponding societal damage metrics to the resilience metrics chosen prior (household dislocation duration and business downtime duration). By determining these quantitative relationships, it would become possible to estimate the effects of different resource distribution strategies on the flood resilience of the community of Lumberton. The regression analysis also made apparent which societal damage indicators were critical for this case study.

Linear regression was chosen as the method of regression analysis for the Lumberton survey data. This is because both household dislocation duration and business downtime duration, here used and referred to as the response (dependent) variables for the regression analysis, are both

continuous variables. If the measure of resilience was a binary (e.g., whether a household was dislocated or not), then a logistic regression would have been more appropriate.

For this case study, the regression analysis of the two societal damage metrics were first performed separately as multiple linear regressions. A multiple linear regression provides a regression model that has more than one predictor, but only a single response variable. There are indications pointing towards the interdependence between the durations of household dislocation and business downtime for a given disaster scenario (for instance, high household dislocation rates can lead to extended business downtime due to a diminished local customer base). Based on this first round of regression analysis, certain societal damage indicators could have demonstrated how household dislocation and business downtime can be related in a multivariate regression analysis.

4.2.2.1 Regression Model Development

Each regression analysis consists of the development of a multiple linear regression model. These models essentially define the coefficients of the societal damage predictor functions. Similarly to the correlation analyses, the statistical development of the regression models was also conducted using the *IBM SPSS Statistics 26* program. However, the development process for the regression models used every societal damage indicator listed in Tables 1 through 4, rather than only the household social vulnerability factors used for the correlation analyses.

The regression model to predict household dislocation underwent development first. As suggested by the name of the model, the response variable of this regression model was household dislocation duration in days. Each other societal damage indicator in Tables 1 and 2 were considered as possible explanatory variables for the household dislocation regression model.

The first step in the regression model development was to compile the raw household survey data into a usable form. Data typically exists in one of four measurement scales, or levels of self-expression: ratio, interval, ordinal, and nominal. Ratio-type data is self-representative; in other words, the value of the data is known without being related to anything else. The value of interval-type data, on the other hand, is dependent on the difference (interval) between data points; singular data points do not have any inherent value. Ordinal-type data is even more dependent on other data in that their value is only represented by being "better" or "worse" than something else, but the interval between data points cannot be computed. Finally, nominal-type data cannot even be compared to anything to determine its relative value, is therefore only defined by its name. A common example of each form of data is as follows: weight (ratio), temperature (interval), the Likert scale (ordinal), and blood type (nominal).

The linear regression analysis conducted here required that the input data take the form of either ratio or interval data. It is necessary for the data points to be numerically comparable to one-another. However, much of the societal damage indicators for Lumberton, and therefore the data collected for each of the corresponding damage metrics, took an ordinal or nominal form (e.g., building ownership, construction material, race and ethnicity). To make these types of data usable in the linear regression analysis, they were converted into dummy variables.

Dummy variables are used to represent ordinal and nominal data in a numerical form using a series of binary values. To represent each possible value of an ordinal or nominal variable, a different combination of ones and zeros are used in the binary series. Take, for example, three home construction materials: wood, masonry, and steel. Construction material would usually be a nominal variable, since each of its three options are not inherently 'better' or 'worse' than each other. To represent home construction material in a numerical form, the original variable is

replaced with two binary dummy variables. The first dummy variable describes whether or not the home is constructed out of wood (1 if it is, 0 if it is not). The second dummy variable does the same, but for masonry. The third option, steel, is represented by these two dummy variables both taking on a value of zero. As shown in Figure 3 below, each construction material is therefore represented by a combination of numbers. Critically, it can be seen the number of dummy variables needed to represent a variable is one fewer than the number of possible values. This is important because explanatory variables in a regression analysis will ideally be as independent as possible. Having too many dummy variables results in one or more of them being linearly dependent on the others.

Material	Dummy 1	Dummy 2
Wood	1	0
Masonry	0	1
Steel	0	0

Figure 3. A nominal variable, consisting of three possible construction materials, is represented as numerical combinations of two dummy variables.

Since each of these dummy variables are binary, they are considered to be ratio-type variables, and can be used in lieu of the original nominal variable in the linear regression analysis. Following this procedure, dummy variables were therefore created for each of the ordinal and nominal variables. The full list of dummy variables for both household and business damage indicators was included in Tables A1 and A2 in Appendix A. The nominal or ordinal option that is represented with using all zeroes was called the “reference” dummy variable, but this variable was not used in the regression analysis. Note that when using dummy variables, all dummy variables pertaining to a particular ordinal or nominal variable must be included or excluded from a regression model together, or they will not have a complete meaning.

With all of the household survey data represented in either ratio or interval form, the next step was to determine which explanatory variables to include in the linear regression model. The inclusion criterion was based on its statistical significance at a confidence level of 95% ($\alpha = 0.05$) based on a two-tailed T-test. First, a regression analysis was conducted on every possible pair of the response variable (household dislocation duration) and each explanatory variable in order to broadly gauge the significance of each explanatory variable. This process was similar to the correlation analysis conducted prior.

Next, all of the explanatory variables for each category of societal damage indicator (building property, socio-economic demographics, etc.) were tested against the response variable using a stepwise procedure. The stepwise procedure is an iterative process which develops a regression model over time, including and excluding explanatory variables on each iteration based on each of their significances. If an unused explanatory variable were determined to be significant, it would be included into the model, and if an explanatory variable already in the model was deemed insignificant, it would be removed. The iterative process is important because the significance of any particular explanatory variable is dependent on the other explanatory variables included in the model. The case may be that two or more explanatory variables "over-explain" the response variable, resulting in one or more of them having poor significance (a p-value greater than α).

Finally, using the observations made regarding the trends in significance for each explanatory variable, a final household displacement duration regression model was developed using a trial-and-error process. Explanatory variables from every category were tested in this version. The value or quality of each tested regression model was evaluated based on its adjusted R square value; the R square term describes the proportion of variance in the response variable

that is predicted by the explanatory variables. A larger R square term implies that the response variable is better predicted by the explanatory variables used. The adjusted R square term accounts for the *chance* predictionality that appears when adding more and more explanatory variables, and is calculated in the *SPSS* program as:

$$R_{adj}^2 = 1 - \frac{(1-R^2)(N-1)}{N-k-1} \tag{3}$$

where N is the number of samples used in the regression model, and k is the number of explanatory variables included.

4.2.2.2 Regression Modelling Results

After testing many combinations of the explanatory variables that were found to be most significant in the previous tests, the final regression model for households was obtained through the trial-and-error process. The dislocation duration experienced by a particular household in Lumberton as a result of flooding due to 2016 Hurricane Matthew can be estimated as:

$$DL_i = 2.606 + R_i + DS_{H,i} + (-20.200) * T_{rent,i} + 0.288 * N_{work,i} \tag{4}$$

$$R_i = 20.739 * r_{Black} + 15.508 * r_{Native} + (-9.491) * r_{other} \tag{5}$$

$$DS_{H,i} = 18.607 * ds_1 + 132.589 * ds_2 + 119.623 * ds_3 + 192.681 * ds_4 \tag{6}$$

where DL_i is the duration of dislocation in days for household i, R_i is the number of dislocation days due to the race of the household, $DS_{H,i}$ is the number of dislocation days due to the overall damage state of the household's home building after flooding, $T_{rent,i}$ is a binary variable equal to 1 if the household is a renter and 0 otherwise, and $N_{work,i}$ is the total number of days of work missed by members of the household as a result of the flooding. Equation (3) uses three binary variables: r_{Black} is equal to 1 if the household identifies as Black only, r_{Native} is equal to 1 if the

household identifies as American Indian only, and r_{other} is equal to 1 if the household identifies any other non-White race, or a combination of races. Equation (4) also uses binary variables, where ds_1 is equal to 1 if the home building was at damage state 1, and et cetera for ds_2, ds_3 and ds_4. The statistical output of the household dislocation duration regression model is included in Tables 12 and 13, and the descriptions of the overall damage states for homes are included in Appendix B, Table B1 (Deniz et al. 2020).

Table 12. Household dislocation duration model summary.

R	R^2	R^2_{adj}	Standard Error of the Estimate
0.673	0.453	0.439	67.533

Table 13. Household dislocation duration model coefficient statistics.

Explanatory Variable	Unstandardized β Coefficient	Standardized β Coefficient	Standard Error	t-value	Significance
$constant$	2.606		6.376	0.409	0.683
r_{Black}	20.739	0.110	9.326	2.224	0.027
r_{Native}	15.508	0.058	12.092	1.283	0.201
r_{other}	-9.491	-0.033	13.015	-0.729	0.466
ds_1	18.607	0.096	8.750	2.127	0.034
ds_2	132.589	0.512	11.412	11.619	0.000
ds_3	119.623	0.281	17.995	6.647	0.000
ds_4	192.681	0.281	28.391	6.787	0.000
T_{rent}	-20.200	-0.099	8.899	-2.270	0.024
N_{work}	0.288	0.192	0.062	4.623	0.000

The household dislocation regression analysis provided some contextual insight into the relative effects of different social vulnerability factors on disaster outcomes. Based on the dataset used for this case study, Equation (4) suggests that renting households would experience fewer days of dislocation versus their homeowner counterparts. This may be explained by renting households being able to move to another property more ‘freely’, as they have less financial attachment to their homes. However, dislocation duration was also dependent on the level of

damage experienced by the home building, which may be lower or higher for rented buildings compared to those occupied by the owner. For household race, Equation (5) suggests that Black households would be most negatively impacted by the flood, whereas the lowest impacts were felt by households identifying as non-White, non-Black, and non-American Indian, or as two or more races ('other'). Notably, overall building damage was observed to have a greater potential in increasing dislocation duration compared to the social vulnerability factors, especially if the level of damage exceeded damage state 1.

With the household dislocation duration regression model created, the same procedure was repeated for the business downtime duration regression model. The downtime duration experienced by a particular business in Lumberton as a result of flooding due to 2016 Hurricane Matthew can be estimated as:

$$DT_i = 1.558 + DS_{B,i} + N_{util,i} + D_{empl,i} + 16.637 * V_{small,i} \tag{7}$$

$$DS_{B\ ,i} = 1.526 * ds_1 + 0.476 * ds_2 + 19.488 * ds_3 + 45.614 * ds_4 \tag{8}$$

$$N_{util} = 0.439 * n_{elec} + 0.176 * n_{other} \tag{9}$$

$$D_{empl} = (-15.831) * d_{empl,property} + 51.627 * d_{empl,mental} \tag{10}$$

where DT_i is the duration of downtime in days for business i, $DS_{B,i}$ is the number of downtime days due to the damage state of the internal contents of the business's building, $N_{util,i}$ is the number of downtime days due to loss of building utilities, $D_{empl,i}$ is the number of downtime days due to difficulties experienced by the business's employees, and $V_{small,i}$ is binary variable equal to 1 if the business is "small" according to the U.S. Small Business Administration (SBA 2019). Equation (6) uses the same binary variables as previously used in Equation (4). In Equation (5), n_{elec} and

n_{other} are the number of days of electric utility loss and other utility loss, respectively, experienced by the business. Finally, Equation (6) uses two binary variables, where $d_{empl,property}$ is equal to 1 if one or more employees experienced damage to their personal property due to flooding, and $d_{empl,mental}$ is equal to 1 if one or more employees experienced mental injury due to the flooding. The statistical output of the business downtime duration regression model is included in Tables 14 and 15, and the descriptions of the internal contents damage states for businesses are included in Appendix B, Tables B3 and B4 (Watson et al. 2020).

Table 14. Business downtime duration model summary.

R	R^2	R^2_{adj}	Standard Error of the Estimate
0.691	0.478	0.443	35.077

Table 15. Business downtime duration model coefficient statistics.

Explanatory Variable	Unstandardized β Coefficient	Standardized β Coefficient	Standard Error	t-value	Significance
$constant$	1.558	-	6.038	0.258	0.797
ds_1	1.526	0.010	9.788	0.156	0.876
ds_2	0.476	0.002	13.269	0.036	0.971
ds_3	19.488	0.119	10.584	1.841	0.068
ds_4	45.614	0.413	7.766	5.874	0.000
n_{elec}	16.637	0.177	6.023	2.762	0.007
n_{other}	0.439	0.146	0.199	2.202	0.029
$d_{empl,property}$	0.176	0.277	0.043	4.139	0.000
$d_{empl,mental}$	-15.831	-0.169	6.053	-2.615	0.010
V_{small}	51.627	0.201	16.764	3.080	0.003

The predictor variables for building downtime have their own relative effects on downtime duration. Recall that these effects are particular to Lumberton and the 2016 floods. The highest binary impact was expected to occur from the mental distress of the business's employees, at 51.6 days. This was surprisingly higher than that for the worst internal contents damage state, at 45.6 days for damage state 4. On the other hand, it appeared that *fewer* downtime days were expected

if the employees experienced personal property damage, though some level of interplay between personal property damage and mental distress may be expected. Otherwise, Equation (7) showed that small businesses in Lumberton were expected to experience longer downtime, and Equation (9) suggests that businesses depend more on electrical utilities than other utilities to avoid downtime.

The regression analysis reduced the number of societal damage indicators from an initial list of 68 to a final 10, five apiece for the households and the businesses. This magnitude of reduction would usually be desirable because it also reduces the amount of data needing collecting. Of course, in the context of this case study, the reduction was not a priority because the data was all collected already. What this regression analysis provided for this case study instead were the functions necessary for predicting the effects of resource distributions to households and businesses. These functions were used in the societal optimization process of step 5.

4.3 Community Portfolio

The third step of the SORD framework is to establish the community portfolio. The primary purpose of the community portfolio is to establish the scope of the resource distribution planning. This is achieved by defining which portions of the target community are considered, either geographically, demographically, or otherwise, and also by defining the scale at which the population of the community is considered, such as at an individual or a census block group level.

The scope of the Lumberton case study is heavily informed by the decisions made in the previous two steps. The population of the community being considered in this case study was the representative survey sample set: 861 households and 217 businesses. As also suggested by the

survey work conducted by the Center, the scale of the resource distribution strategy design was individual households and businesses.

The creation of the community portfolio within the SORD framework would generally culminate with the collection of the relevant data. The types of data required is defined by the set scope and scale, as well as the societal damage indicators chosen in the second step. For this case study, it only follows naturally that the Lumberton Wave 1 and Wave 2 survey data be used. This dataset includes both information on the chosen affected population, as well as information regarding the affected buildings and built environment used by this population.

4.4 Resource Types and Amounts

In step 4 of the SORD framework, the user is required to choose to use either or both disaster mitigation resources and disaster recovery resources. Both are applicable for enhancing community disaster resilience. The clear difference is the timeframe of when these resources are applied to the community; mitigation resources should be disbursed pre-event, and recovery post-event.

4.4.1 Resource Types

Pre-event disaster mitigation resources were used in the Lumberton case study. For households, the resource took the form of a structural retrofit. The structural retrofit was the elevation of the home building to above the anticipated floodwater levels for the given hazard intensity. By removing the building from the floodwaters, it is expected that the home experiences no physical damages. Recall that despite that the floodwaters in Lumberton were caused by a hurricane, high winds from the coastal storm were not a concern for the inland city. This was also in line with the hazard type chosen in step 1, which was stated as riverine flooding only. A cost

breakdown for all business retrofit scenarios are outlined in Tables 12 and 13. These retrofit costs are dependent on the initial internal damage state of the business, as recorded in the business survey data, and the final internal damage state as chosen through the optimization in the next section. This section provides the detailed account of how each of the values listed in Tables 12 and 13 were obtained.

Table 16. Retrofit costs for protecting household homes and business inventory and equipment, as a function of initial and final damage states.

Initial damage state	**Final damage state**	**Cost of elevating home building**	**Cost of protecting business inventory and equipment**
DS 4	DS 3	$88,000	$94,000
	DS 2		$112,000
	DS 1		$129,000
	DS 0		$129,000
DS 3	DS 2		$112,000
	DS 1		$129,000
	DS 0		$129,000
DS 2	DS 1		$94,000
	DS 0		$94,000
DS 1	DS 0		$94,000

Table 17. Retrofit costs for installing a standby generator function of expected floodwater height.

Expected floodwater height at building	**Cost of generator and platform**
> 96 in.	$0*
≤ 96 in., > 72 in.	$79,900
≤ 72 in., > 48 in.	$70,000
≤ 48 in., > 24 in.	$61,800
≤ 24 in., > 0 in.	$55,400

*Generator cannot be raised high enough and is therefore not installed.

A review of historical reports was conducted in order to estimate the cost of these structural retrofits. Two main sources were used to establish this cost, recorded bids from contractors and FEMA grant disbursements for similar elevation projects from across North Carolina. An agenda item from the Lumberton, NC, city council published online showed a summary of the lowest bids received by the city's planning department for the elevation of six homes (City of Lumberton 2019); the low bids ranged from $85,000 to $172,260 for home sizes ranging from 988 square feet to 2,133 square feet.

The second source provided a much larger sample set to pull from, it being the FEMA Hazard Mitigation Assistance Projects (HMAP) dataset (FEMA 2019b). This dataset lists every project which has been funded as an HMAP through one of several funding programs including the FEMA Hazard Mitigation Grant Program (HMGP). The purpose of the grant program is to provide federal funding to communities across the United States to implement hazard mitigation measures following Presidential Major Disaster Declarations in the area; home elevation is an example of one of many mitigation projects funded through the HMGP.

For the purposes of this case study, the HMAP dataset was filtered to highlight funded projects involving Elevation of Private Structures – Riverine, located in North Carolina. An average cost of $88,000 per home was calculated by comparing the funding amount with the final number of buildings covered by each grant. This calculated value falls within the range previously established using the six low bids. The estimated cost of elevation of $88,000 per home was ultimately adopted as the cost of this type of retrofit for this case study. This value was chosen based on a larger sample size of previous projects, which included projects in Lumberton and surrounding areas needed after Hurricane Matthew. Unfortunately, the dataset did not include

sufficient detail to consider home size or elevation height. Therefore, the $88,000 cost was used for each home being retrofitted in the case study.

The home elevation retrofit resource was implemented in this case study by reducing the expected damage state of the retrofitted home to zero. The resulting effect on the resilience measure, household dislocation duration, can thus be calculated through the use of the regression equation obtained in the previous step. Not every household surveyed needed this retrofit, as the level of damage they experienced varied; choosing which households would receive the retrofit resource was the purpose of the optimization step.

For businesses, similar resources were implemented. However, the large variety of business building layouts and sizes made using a general elevation retrofit unreasonable. In addition, the regression model for business downtime duration used the internal damage state of the building, rather than for the building overall. The chosen alternative was to use smaller retrofits to either elevate only the internal contents of the buildings, including inventory, machinery, and equipment, on an elevated steel-framed platform. A second option of constructing a waterproof room for these items to reside in (if the expected flood height is too high for elevation inside the building to be effective) was also made available. While this type of retrofit does not protect the building itself when flooding occurred, it does minimize the losses incurred from inventory loss or equipment replacement. Note, however, that the retrofit level for businesses was allowed to vary; while the households are automatically retrofitted to a no damage state if elevated, the final damage state of the business could be set to an intermediate level at a lower retrofit cost.

The costs of these retrofits were informed using a mitigation plan published by the Department of City Planning of the City of New York (2018).

An additional retrofit resource was also made available for businesses in the form of standby generators. The purpose of these generators is to provide auxiliary power to the business in the event of electric utility loss. The regression model developed in step 2 showed that business downtime can be reduced substantially by minimizing days of electric utility loss, for example by powering computers and other electrical devices or by maintaining refrigeration systems. For the standby generators to remain effective, they must also be placed above the impending floodwaters; much like the household retrofits, intermediate levels of retrofit for standby generators (partial inundation) were not acceptable. In the same way that the inventory and equipment could be elevated, the generator can be protected to become effective as soon as possible after the flooding occurs. The aforementioned New York mitigation plan also provides cost guidelines for the elevation of generators on either steel or concrete platforms (City of New York 2018). The final cost involved is the cost of the standby generator itself. Based upon publicly advertised costs online from a variety of retailers, an estimated cost of a 60 to 80 kW standby generator was taken as $20,000.

There was one final resource that had been examined in this case study. As noted earlier, a levee system was built along the Lumber River to protect the southwestern portion of Lumberton, though with a crucial flaw in the form of an overpass opening underneath Interstate 95 (Figure 4). A floodgate was originally considered to be built to properly secure this opening but was never constructed in time to prevent the inflow of floodwaters in 2016, or even later in 2018.

Figure 4. View of the Interstate 95 overpass opening in the Lumber River levee system in May 2019, crucially lacking a floodgate system. Image taken from *Google Street View*.

The final resource was therefore the retrofit of the levee system, or specifically the installation of a floodgate at the I-95 overpass. Preliminary estimates made by the North Carolina Emergency Management for the flood gate installation cost came to $486,000 (NCEM 2018), though a recovery plan prepared by the Hurricane Matthew Disaster Recovery and Resilience Initiative at the University of North Carolina at Chapel Hill (2018) cited a cost estimate of approximately $2.5 million for the flood gates. However, a more recent statement made in 2019 by the Lumberton Public Works director Rob Armstrong suggested the cost would be even higher at $4 million to $5 million (Bigelow 2019).

In order to use the entire levee system as a mitigation resource, the cost of the levee and the associated watershed improvements were also considered. Records for the original construction of the 2.8 mi long levee, which began in the 1960's (FEMA 2005), proved to be difficult to find. Instead, costs of similar earthen levee projects in the United States were examined

(United States Army Corps of Engineers 2008, Smith 2011, City of West Sacramento n.d.), averaged per mile cost, and adjusted using the RS Means 2019 Location Factor for Lumberton (The Gordian Group Inc. 2018). An average cost of $27 million was taken as the cost for the construction of the levee itself. The costs of the watershed improvements for the Lumber River levee, referred to as U.S. Soil Conservation Service Project 40054 – Watershed Work Plan Jacob Swamp Watershed, was recorded to cost $329,695 in 1966, or $2,625,054 in 2020 dollars (Committee on Government Operations 1971). In total, the cost of the levee including floodgates was taken as $34.6 million.

Overall, three types of resources were used in this case study; household retrofits, business retrofits, and the levee. Note that all three of these resource types affects only the damage state term in the regression equations established in the previous step. Other resource types may be found more appropriate for other scenarios, such as a disbursement of monetary funds or managing emergency workers.

4.4.2 Resource Amounts

With the resource types determined, the next step was to determine the amounts of resources. The relative distribution of resources was sought at this step rather than a deterministic quantity of resources. This was the stage at which the different types of societal fairness were implemented into the resource distribution strategies. In order to evaluate the effectiveness of using optimization as part of the SORD framework, both equal and equitable forms of resource distributions were developed. Equal distributions were defined as disbursing an equal amount of resources to each member (household or business) of the population, whereas the goal of the equitable distributions was to make the outcomes of the resource distribution as equal as possible. These outcomes were defined using the resiliency metrics, household dislocation duration and

business downtime duration. If each member of the population had the exact same dislocation or downtime duration, the resource distribution leading to this scenario would be described as being perfectly equitable.

In addition to the equality and equity forms of societal fairness, a 'semi-equitable' condition was also considered. This intermediate condition differentiated between households and businesses based on if they were damaged, but not by the level of damage. Additionally, the semi-equitable condition did not consider the remainder of the socio-economic factors that were expected to influence a community's resilience. The different combinations of retrofit types and societal fairness led to a total of nine resource distribution strategies which are listed in Table 14.

Table 18. Resource distribution strategies considered for the Lumberton case study.

Strategy	Resource	Relative distributions
1	Levee system	Equal; all homes and businesses are protected by the levee
2	Household retrofits	None; no homes are retrofitted
3		Equal; all homes are retrofitted
4		Semi-equitable; all damaged homes are retrofitted
5		Equitable; distribution is societally optimized
6	Business retrofits	None; no businesses are retrofitted
7		Semi-equitable; all damaged businesses are retrofitted
8		Equitable; distribution is societally optimized
9	Household and business retrofits	Equitable; household and business equity metrics are approximately equal

Note that an equality-based strategy was not considered for the business retrofits resource. This was because the retrofit costs for each business differed based on the level of flood damage that was expected to be seen at their respective locations. Thus, in contrast to the equality-based household retrofit option where each home could be retrofitted at an equal cost, the of retrofitting all businesses did not result in equal (cost-wise) resource distribution.

Most of the resource distribution strategies, specifically those with 'None', 'Equal' and 'Semi-equitable' distributions, would have been able to be resolved at this stage of the framework. The distribution solution for each of the six relevant strategies was defined by their descriptions, as seen in Table 14. This was not the case for the 'Equitable' strategies, hence prompting the use of optimization step of the SORD framework.

4.5 Optimization

The design of equitable resource distributions is an iterative process which calls for the use of optimization. Iterations were required because of how equity was defined in this case study in section 4.4; the level of equity for a particular resource distribution was unknown until the outcomes of that resource distribution were calculated. Since there were innumerable possible resource distributions that could be tested, optimization was the ideal method of determining the most equitable solutions. An optimization procedure called Genetic Algorithm optimization was chosen and implemented as a MATLAB code for this case study.

4.5.1 Genetic Algorithm Optimization

For this case study, Genetic Algorithms (GAs) was chosen as the optimization procedure. GA optimization is a technique which imitates the natural process of evolution; incorporated in the GAs are the processes of reproduction, chromosomal crossover and genetic mutation (Figure 5). These biological processes are across a population of individuals (solutions, or in this case, resource distributions), each of which are defined using strings of digitally-encoded chromosomes. Each of these chromosomes, or positions along the string, represents a quality of the individual. In the context of this case study, chromosomes include qualities such as building damage state, income, and recovery status.

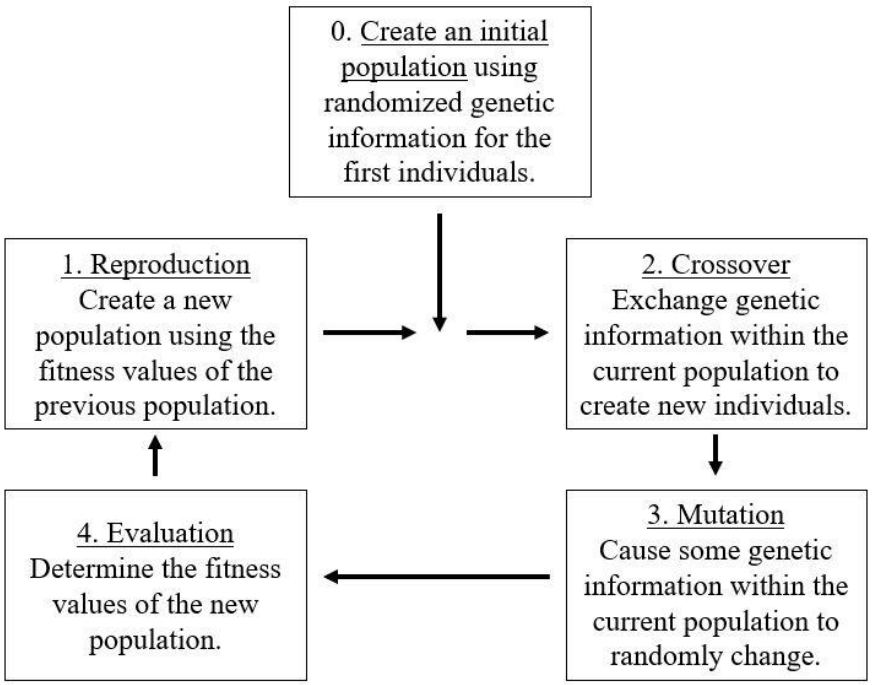

Figure 5. Basic schematic of a generic Genetic Algorithm optimization procedure.

Optimization using GAs has some advantages over other optimization procedures (Goldberg 1989). GAs are able to search across a large domain using an inherently diverse initial population of solutions, which is important when there is little knowledge of what the solution (resource distribution) should look like. In addition, by searching across a large domain, local optima can be avoided to find the global optimum. GA optimization also uses an objective (fitness) function to drive its search, rather than depending on derivatives or gradient functions which can be difficult to calculate or otherwise determine. The fitness function describes the value or worth of a given solution; greater fitness values imply that its associated solution is closer to the global optimum. Finally, GA optimization uses stochastic transition rules in lieu of deterministic transition rules, which also helps avoid local optima, as well as making GA optimization less susceptible to possible modeling errors in said transition rules.

The optimizations for each of strategies 5, 8 and 9 in Table 14 were conducted separately. This meant that the populations for each optimization process consisted of only households, only businesses, and finally both households and businesses, for strategies 5, 8 and 9, respectively. The individuals of the populations studied using the GAs were defined using strings with length equal to the number of households or businesses: strings with length of 861 digits for households, and 217 digits for businesses. Each position along these strings appropriately represented a household or business, and more specifically, represented the final damage state for that household or business using a base 5 digit (there being four possible damage states for each household or business plus a no-damage state). These final damage states were determined by the amount of resources received by each household or business. In summary, each string (individual) in the population represented one possible resource distribution.

4.5.1.1 Genetic Algorithm Reproduction

For each iteration in this optimization, the population of strings underwent the processes of reproduction, crossover and mutation. Reproduction is the step of forming the new population for the current iteration, typically on the basis of the fitness of each individual. In this case study, new populations were formed by using the "remainder stochastic selection without replacement" method. This method operates over three steps; first, the fitness ratio of each individual of the old population is calculated by dividing their associated fitness value by the total fitness of the entire population. Second, each fitness ratio is multiplied by the desired population size; for this case study, the population size was set to be constant throughout each iteration but varied between optimization tests for a parametric study. The whole number portion of the product is the guaranteed number of offspring for the individual the fitness ratio belongs to; that many copies of the individual will definitely be included in the new population.

As suggested by the name of the method, the fractional portion of the product (the "remainder") is used to stochastically determine the rest of the population in the third step. To do so, the probability that each individual will reproduce is set equal to its remainder. The individuals are then sorted from largest to smallest probability. Finally, for each offspring needed to form the rest of the new population, each individual is stochastically tested consecutively to see if it reproduces. If an individual reproduces, a copy of it is introduced into the new population, the individual is removed from the reproduction pool, and the stochastic testing repeats with the new reproduction pool, until the new population is formed.

4.5.1.2 Genetic Algorithm Crossover

Once the individuals of the new population were determined using the reproduction process, crossover occurred. In biology, crossover is the process in which genetic material swaps between a pair of DNA molecules the parents of an offspring to create the child's DNA. A similar process was applied to the individual strings of the GA optimization population. Crossover in GA optimization is done by forming pairs of individuals from the population, choosing a random crossover site for each pair, then swapping the string values in the crossover site between the pair of individuals. Crossover will not always occur for each individual pair; a stochastic test is applied for each pair, during each iteration, based on a global probability of crossover. For this case study, the probability of crossover was set at 0.3. The purpose of crossover is to create new individuals using the genetic information of successful (high fitness) parents, with the possibility of combining the most desirable attributes of each parent. Without crossover (or mutation), no new individuals could be tested in the GA optimization, meaning the optimization domain would be severely limited.

4.5.1.3 Genetic Algorithm Mutation

The last process of the GA optimization was mutation. As is the case in biology, mutation is the random change in the genetic material of an individual. Based on a global probability of mutation, each position along each string in the population was tested to see if it would mutate. If mutation did occur, the value of the string position would be replaced with a new, randomly chosen value. Various probabilities of mutation were tested in this case study, based on how quickly the solutions converged to an optimum; a mutation probability of 0.001 was deemed appropriate. Similarly to crossover, mutation allows for the creation of new individuals that would could not appear otherwise; it also helps the algorithm from converging on local optima by periodically expanding the domain of solutions.

4.5.2 Predictor and Fitness Functions and Constraints

In order to apply optimization to the case study, a predictor function and a fitness function were needed. The predictor function was used to determine the outcomes of the resource distributions developed through the GA optimization procedure. In this case study, the regression models developed in step 4 served as the predictor functions, each able to determine the resulting household dislocation duration or business downtime duration for a given resource distribution.

The fitness function was used to evaluate the outcomes (equity) of the resource distributions. The equation form of the general fitness function was provided as Equation (1) in Section 3.5. In this case study, the equity of a solution was defined to be how equal the outcomes of the resource distributions were across all households or businesses. Mathematically, equity was calculated to as the average difference between household dislocation durations or business downtime durations across all households or businesses. The associated fitness function then

became the inverse of this average difference, as the goal of the optimization was to maximize the fitness function. The mathematical form of the equity measure and the fitness function are presented as Equations (11) and (12), respectively.

$$x_{equity} = \frac{1}{N^2 - N} \sum_{i,j=1}^{N} \left| DD_i - DD_j \right|, i \neq j \tag{11}$$

$$f_{fit}(x) = \frac{1}{x_{equity}} \tag{12}$$

where x_{equity} is the equity measure, N is the number of households or businesses considered, and DD_i is the dislocation duration or downtime duration for household or business i, respectively.

A constraint on the resource distributions was also put into place during the optimization in the form of a maximum allowable total cost. This constraint, shown mathematically as Equation (13), allowed for more control over the resource distributions being considered.

$$cost_{max} > \sum_{i=1}^{N} cost_i \tag{13}$$

where $cost_{max}$ is the maximum allowable total cost, N is the number of households or businesses considered, and $cost_i$ is the cost of the resources provided to household or business i. For the case study, the equitable distributions for households and businesses were first optimized with two maximum costs; once each with no cost limit, and then again with a somewhat arbitrary cost limit equal to the total cost of the levee ($34.6 million).

For GA optimization, it is desirable to keep as much information as possible in the populations being studied. In other words, just because an individual solution in the population violates the constraint does not mean that its genetic information is not useful. Take as a quick

example of a resource distribution with an extremely high fitness value, but with total cost of $35 million; while the cost constraint is exceeded, clearly there are some patterns in the string of the resource distribution that can be useful if crossed-over into another string. In order to keep such invalid solutions in the genetic pool without them being considered optimal, penalty functions can be applied to their fitness value. The penalty function used for this case study is as follows: if the cost of the resource distribution string exceeds the total cost constraint, the fitness value is halved. Therefore, if the offending string had a high fitness, its traits are kept in the genetic pool for at least one more generation. The revised constraint and penalty function therefore becomes:

$$cost_{total} = \sum_{i=1}^{N} cost_i \tag{14}$$

$$if\ cost_{total} > cost_{max}, then\ f_{fit,p} = \frac{1}{2} f_{fit} \tag{15}$$

where $cost_{total}$ is the total cost of the resource distribution, N is the number of households or businesses considered, $cost_i$ is the cost of the resources provided to household or business i, $cost_{max}$ is the maximum allowable total cost set by the user, and $f_{fit,p}$ is the penalized fitness function. When the penalized fitness function is calculated, it is used in lieu of the original fitness function.

It is important to note that for the purpose of this case study, comparing between equality- and equity-based resource distributions was the main goal rather than minimizing costs or maximizing cost efficiency. Hence, the fitness function used was solely based on the average difference in dislocation or downtime duration, and not of any associated monetary cost. However, the solutions could still be judged as a function of expected cost, as can be seen in section 4.6.

4.5.3 Optimization Summary

Since GA optimization is an iterative process, the procedure must be repeated until the results converged on an optimum solution. The rate of convergence depended on the population size and the probabilities of crossover and mutation. Here, convergence was seen after approximately 500 generations for a population size of 300, a crossover probability of 0.3, and a mutation probability of 0.001 (Figure 6).

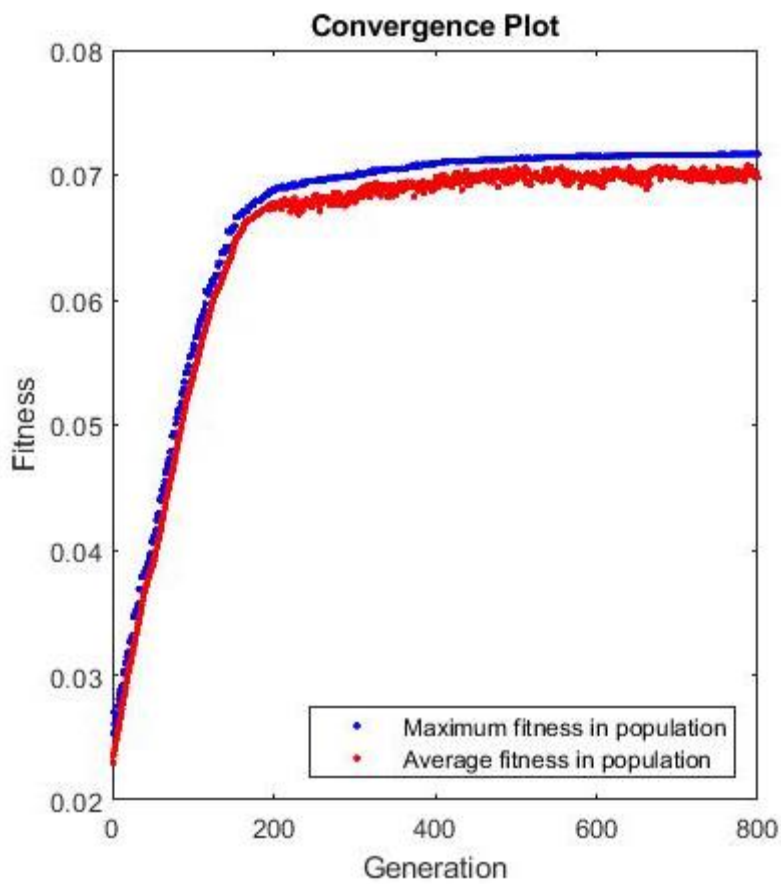

Figure 6. Maximum and average fitness of a population of household resource distributions optimized for equity over 800 generations (iterations).

Accounting for the constraints, a total of five optimizations were conducted; two apiece for households and for businesses, and one for a combined households and businesses, as outlined in

Table 15. The strategy numbers correspond to those used in Table 14, where ‘a’ and ‘b’ differentiate between the cost constraint used. Note, however, that the costs of the business retrofits did not approach the maximum cost constraint, and therefore strategies 8a and 8b are identical. Figures D1 through D10 in Appendix D presents the populations of optimized resource distribution solutions for the remaining four different strategies. Note that the chosen solution was based solely on maximum equity (lowest average difference in downtime or dislocation duration).

Table 19. Optimizations conducted for the Lumberton case study.

Strategy	**Description**	**Maximum fitness value**	**Average difference in downtime or dislocation duration**	**Cost of retrofits**
5a	Household retrofits, max cost of $34.6 million.	0.0717	14.0 days	$34,584,000
5b	Household retrofits, no maximum cost.	0.0725	13.8 days	$37,752,000
8a	Business retrofits, max cost of $34.6 million.	0.0605	16.5 days	$14,963,700
8b	Business retrofits, no maximum cost.	0.0605	16.5 days	$14,963,700
9	Household and business retrofits, max combined cost of $34.6 million.	Households: 0.0604 Businesses: 0.0599	Households: 16.6 days Businesses: 16.7 days	Households: $23,469,000 Businesses: $10,710,300

As noted earlier, equity was measured as the average difference in household dislocation duration or business downtime duration, where a lower average difference implied a more equitable outcome. The outcomes of the optimizations thus suggested that greater equity could be achieved in Lumberton households compared to the city’s businesses. In addition, the cost constraint used for the household optimization (strategy 5a) did not appear to be meaningful, with the unlimited cost option (strategy 5b) improving equity by only an average of 0.2 days difference

in dislocation duration for a 9% increase in cost. Finally, a suitable solution for strategy 9 was found with an average difference in dislocation and downtime durations at approximately 16.6 days.

4.6 Evaluation of the Resource Distribution Strategies

The last step in the SORD framework is to evaluate the different resource distribution strategies that were developed. In this Lumberton case study, a total of ten strategies were developed, and are summarized in Tables 16 and 17 below. Table 16 includes the total cost of each distribution strategy, its effectiveness represented as a measure of equity (average difference in days of dislocation or downtime), and a cost-effectiveness measure of increased equity (reduction of the average difference in days) per $1 million spent. Table 17 includes additional information regarding the average cost of the retrofits across all households or businesses, as well as the predicted number of days of dislocation or downtime accounting for the retrofits. Equity and increase in equity for strategies 2 through 9 are also compared graphically in Figure 7, as are average costs versus reduction of dislocation/downtime in Figure 8.

Perhaps the most obvious outlier amongst the strategies is the first, the Levee option. This strategy was difficult to evaluate against the other strategies due to its unique conditions. First, its measure of perfect equity assumes that the levee system functions flawlessly in the face of Hurricane Matthew-level flooding to fully preserve the buildings behind it. Second, the exact number of buildings protected by the levee is unknown, though it is expected that this number would be much greater than the 1,078 households and businesses in the survey data. For instance, a hydrologic and hydrodynamic flood simulation completed at Colorado State University suggests that as many as 2,359 residential buildings could have been flooded (Nofal and van de Lindt 2020). Third, the cost of the levee used in this analysis presumes that the levee would have been built at

present times, whereas in reality the majority of the cost (other than the floodgate under I-95 and possible upgrades) would likely be able to be avoided. Despite these unknowns, it is reasonable to assume that the levee option could be the most cost-effective flood mitigation strategy amongst those considered in this case study, if indeed it could prevent all flooding of west and south Lumberton.

For the household retrofit strategies (strategies 2 through 5b), there appears to be minimal effect on the equity measure when comparing between the equality, semi-equity and equity solutions. However, the difference in the costs of the semi-equity (strategy 4) and equity (strategy 5b) options suggest that money could be spent more efficiently to achieve very similar results. Savings of approximately $2.5 million, or about 6.3%, led to the same level of equity (13.8 days average difference) and a very slight increase in total dislocation time. When the cost constraint was applied (strategy 5a), the overall outcome was only slightly less equitable than the unconstrained strategy. On the other hand, the increase in equity per $1 million metric actually showed that the cost constrained option was more cost-efficient than any of the other household resource distribution strategies, reducing the average difference in days of dislocation by -1.42 days per $1 million, and the total days of dislocation by 984 days per $1 million.

The business strategies had similar patterns in their outcomes. Strategy 8, the equity option for businesses, was only more equitable by 0.6 days average difference compared to the semi-equity option of fully retrofitting all potentially-damaged businesses. The total number of days of downtime was higher for the equitable resource distribution, in the same trend as for the household retrofits. However, it was also again the more cost-efficient method, with an increase in equity of -0.93 days per $1 million (versus -0.74 days for strategy 7) and a greater reduction in total downtime by 16 days per $1 million.

Table 20. Costs and equity of all resource distribution strategies considered in the Lumberton case study.

Strategy	Description	Total Cost	Equity[1]	Increase in Equity[2]
1	Levee (Equality) All buildings protected using a levee system.	$34,600,000	0 days difference	-
2	Households (Do nothing) No homes are retrofitted.	$0	63.0 days difference	-
3	Households (Equality) All homes are retrofitted.	$189,464,000	13.8 days difference	-0.26 days / $1 million
4	Households (Semi-equity) Homes expected to be damaged are retrofitted.	$40,304,000	13.8 days difference	-1.22 days / $1 million
5a	Households (Equity, max cost) Homes are retrofitted equitably, with a maximum cost of $34.6 million.	$34,584,000	14.0 days difference	-1.42 days / $1 million
5b	Households (Equity, no max cost) Homes are retrofitted equitably, with no maximum cost.	$37,752,000	13.8 days difference	-1.30 days / $1 million
6	Businesses (Do nothing) No businesses are retrofitted.	$0	30.4 days difference	-
7	Businesses (Semi-equity) Buildings expected to be damaged are retrofitted.	$17,981,700	17.1 days difference	-0.74 days / $1 million
8	Businesses (Equity) Buildings are retrofitted equitably, with no maximum cost.	$14,963,700	16.5 days difference	-0.93 days / $1 million
9	Households and Businesses (Equity) Homes and businesses are retrofitted such that their equity metrics are approximately equal, with a maximum combined cost of $34.6 million.	$ 34,206,300	16.7 days difference	-1.63 days / $1 million

[1]Equity was measured by the average difference in downtime or dislocation duration across all homes or businesses, respectively.
[2]The increase in equity was calculated in relation to the Do Nothing strategies 2 and 6.

Table 21. Costs and dislocation/downtime duration of all resource distribution strategies considered in the Lumberton case study.

Strategy	Description	Total cost	Average cost per household / business	Dislocation / downtime duration		Reduced dislocation / downtime[3]
				Total	Average	
1	Levee (Equality)	$34,600,000	-	0 days	0 days	-
2	Households (Do nothing)	$0	$0	43,087 days	63.0 days	-
3	Households (Equality)	$189,464,000	$88,000	8,655 days	13.8 days	182 days / $1 million
4	Households (Semi-equity)	$40,304,000	$46,811	8,655 days	13.8 days	854 days / $1 million
5a	Households (Equity, max cost)	$34,584,000	$40,167	9,043 days	14.0 days	984 days / $1 million
5b	Households (Equity, no max cost)	$37,752,000	$43,847	8,674 days	13.8 days	912 days / $1 million
6	Businesses (Do nothing)	$0	$0	5,907 days	30.4 days	-
7	Businesses (Semi-equity)	$17,981,700	$82,865	3,172 days	17.1 days	152 days / $1 million
8	Businesses (Equity)	$14,963,700	$68,957	3,399 days	16.5 days	168 days / $1 million
9	Households and Businesses (Equity)	Households: $23,469,000	Households: $27,187	11,385 days	16.6 days	1,350 days / $1 million
		Businesses: $10,710,300	Businesses: $49,356	3,435 days	16.7 days	231 days / $1 million

[3]The reduced dislocation or downtime was calculated in relation to the Do Nothing strategies 2 and 6.

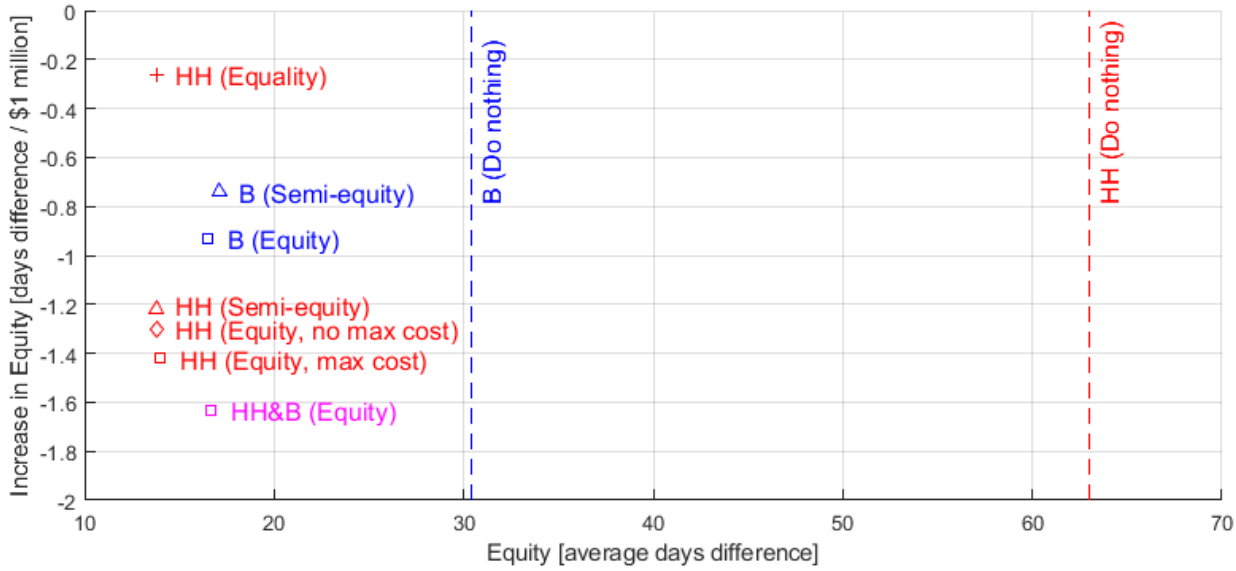

Figure 7. Equity and Increase in Equity for strategies 2 through 9, where HH is households and B is businesses. A lower average days difference and a more negative days difference per $1 million (closer to the bottom left) is more desirable.

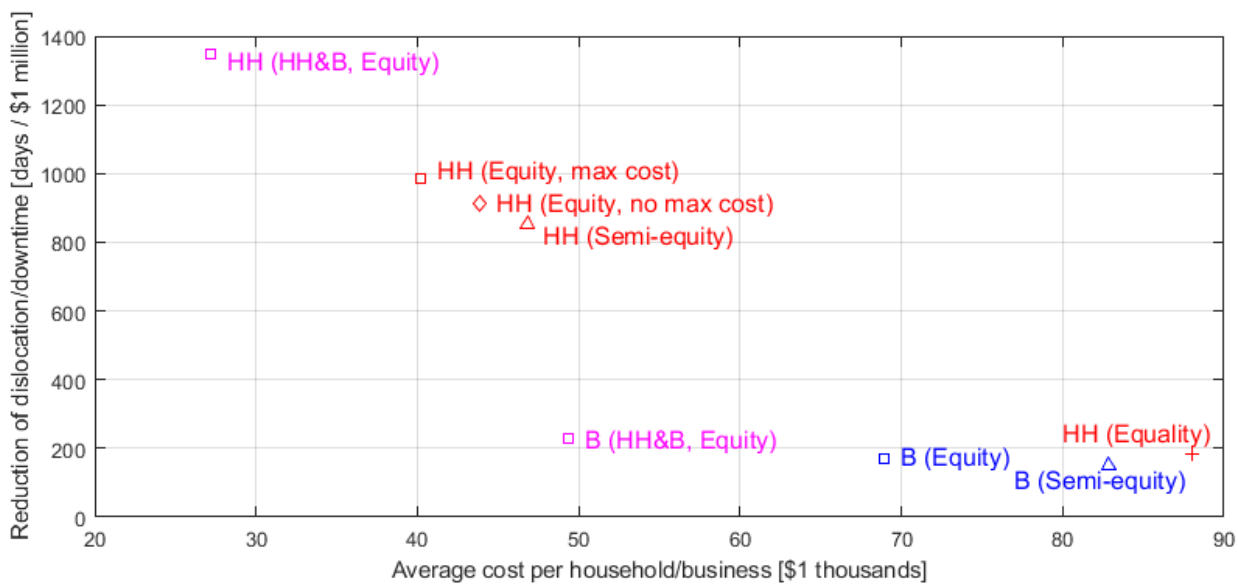

Figure 8. Average cost and reduction of dislocation/downtime for strategies 3 through 9, where HH is households and B is businesses. A lower average cost and a larger reduction of dislocation/downtime (closer to the top left) is more desirable.

Finally, the last strategy combined both household retrofits and business retrofits to achieve similar levels of equity across both groups. Overall, this solution resulted in a greater number of

days in both total household dislocation and total business downtime. It was also slightly less equitable for businesses, and substantially less equitable for the households. Cost-wise, however, strategy 9 managed to have the highest increase in equity per $1 million and highest reduction in both dislocation and downtime per $1 million, despite its lower overall costs and average costs per household or business.

In this case study, equity was defined as the average difference in days of dislocation or downtime amongst all households or businesses, respectively. However, this metric is not the method of gauging the equity of a resource distribution strategy. Another method is to observe the range of dislocation or downtime duration across the population; a highly equitable strategy would theoretically result in a minimal range. The range of dislocation and downtime durations across the considered households and businesses are presented in Table 18.

Immediately visible is each strategy having at least one household or business with no dislocation or downtime. This is consistent with the data collected through the surveys. In addition, there was limited variation in the maximum durations for both households and businesses. This occurred because the potential reduction in expected dislocation or downtime duration by structural retrofits was limited. The dislocation duration of the household(s) with the maximum duration was reduced by only 18.6 days (6.3% of the unmodified dislocation duration), which corresponds with reducing the overall damage state from damage state 1 to damage state 0 as shown in Equation (6). The vast majority (93.7%) of their dislocation duration was therefore caused by other non-structural damage factors. For businesses, the maximum duration was reduced by 45.6 days, which corresponds with reducing the interior damage state of the business from damage state 4 to damage state 0 as shown in Equation (8). In the case of this business(es), a

greater portion (28.9%) of their expected downtime duration was attributed to building interior flood damages.

The results in Table 18 were the best possible scenarios, given that only building retrofits were used as resources in this case study. Other types of resources must be considered to reduce the ranges of dislocation and downtime durations further.

Table 22. Range of dislocation and downtime durations across the considered community population for each resource distribution strategy in the Lumberton case study.

Strategy	**Description**	**Equity[1]**	**Dislocation/downtime duration experienced by an individual household/business**	
			Minimum	**Maximum**
1	Levee (Equality)	0 days difference	-	-
2	Households (Do nothing)	63.0 days difference	0 days	297.7 days
3	Households (Equality)	13.8 days difference	0 days	279.1 days
4	Households (Semi-equity)	13.8 days difference	0 days	279.1 days
5a	Households (Equity, max cost)	14.0 days difference	0 days	279.1 days
5b	Households (Equity, no max cost)	13.8 days difference	0 days	279.1 days
6	Businesses (Do nothing)	30.4 days difference	0 days	157.9 days
7	Businesses (Semi-equity)	17.1 days difference	0 days	112.3 days
8	Businesses (Equity)	16.5 days difference	0 days	112.3 days
9	Households and Businesses (Equity)	16.7 days difference	Households: 0 days Businesses: 0 days	Households: 279.1 days Businesses: 112.3 days

[1]Equity was measured by the average difference in downtime or dislocation duration across all homes or businesses, respectively.

5. Summary and Conclusions

In this dissertation, a new framework for integrating societal justice with civil engineering into resource distribution was proposed. The Societally-Optimized Resource Distribution framework was developed for the study and implementation of community disaster resilience. As the name implies, the SORD framework relies upon the optimization of resource distribution strategies on the basis of the societal factors of the target community. The need and motivation for the development of the framework introduced this dissertation, with a special focus on flood disasters in the United States.

To provide context to the problem statement and the SORD framework, a number of concepts were introduced and discussed. Resilience, a term used in many fields of study, was defined at a systems-level using the 'four Rs' coined by Bruneau et al. (2003). The concept of resilience was further contextualized for this dissertation as community disaster resilience, along with the role of buildings and sustainability in this application of resilience. The idea of societal fairness and its possible forms were then proposed as desirable outcomes of community disaster resilience. This hypothesis formed the basis of a problem statement which asked if the pursuit of societal fairness as an objective in community disaster resilience was practical. Finally, the SORD framework was introduced as a method for addressing the question stated in the problem statement, along with an accompanying case study, and a description of the audience for which the research presented was intended for.

Before the SORD framework could be fully presented, a literature review for this multidisciplinary field of research was required. First, an overview on the study of community disaster resilience and recovery was provided, with emphasis its associated models and outcome measurement methods. The literature review then focused on the societal damage indicators that

have been used historically for characterizing the communities themselves, as well as how they have been measured to qualify community characteristics such as vulnerability to natural hazards and social vulnerability. The first part of the literature review ended by examining the state of research on resource management for disaster recovery.

The second half of the literature review focused on the mitigation of and recovery from flood disasters. Along with a summary of the relevant documentation published by FEMA, other studies performed on flood mitigation practices reviewed. Perhaps most importantly, the established methods for assessing the efficacy of the flood mitigation methods were also examined. The literature review culminated with an exploration of the studies that had been conducted on societal damages and inequalities observed in the aftermath of recent flood disaster worldwide. Ultimately, the literature review demonstrated that a clear disconnect existed between societal fairness and its implementation in disaster resource management.

With the need for the SORD framework made clear, the purpose and methodology of the framework was explained as six major steps. The first step of the framework is to classify the type and intensity of the hazard that is being addressed. Second, the user is required to choose a set of societal damage indicators and metrics to characterize their community. Next, the target population and scale of analysis needs to be decided. A discussion on possible types of population data and built environment data was provided to help the framework user make their decisions.

Once the user has established the details of the hazard and the community, in addition to how the analysis will be conducted, the user will decide the types of resources and resource distribution strategies they wish to consider. These will usually be defined according to the hazard type, and denoting the desired outcomes of the resource distributions, such as achieving one or more types of societal fairness (e.g., equality, equity). The types of resource distribution strategies

chosen will also inform how to conduct the optimizations in the following step. The optimization process, which generates the resource distributions that can be applied in the community, requires fitness and predictor functions, which in turn are dependent on the resource distribution strategies and societal damage metrics, respectively. Once the resource distributions are obtained through optimization, the last step of the SORD framework can be completed, which consists of evaluation and decision-making.

An example walkthrough of the six steps of the SORD framework was presented using a case study of the 2016 flooding in Lumberton, NC. The small but highly diverse city is situated on the banks of the Lumber River, a watercourse which experience immense swelling following intense rains during 2016 Hurricane Matthew and later in 2018 from Hurricane Florence. The case study was able to be conducted using survey data collected by the NIST Center of Excellence for Risk-Based Community Resilience Planning which is operating an ongoing longitudinal study on the city's recovery after the two floods. The SORD framework was exemplified using the 2016 Hurricane Matthew flood scenario in particular.

Following the SORD framework, a list of potential societal damage indicators were first identified based on the information made available by the Center. Societal damage metrics associated with these indicators underwent two statistical analyses: 1) a correlation analysis to investigate the intersections of various household social vulnerability factors as a function of time, and 2) a regression analysis with the purpose of creating predictor functions that can estimate the outcomes of the floods using the community's socio-demographic factors and the resource distribution used. From the first, the correlation analysis, many of the social vulnerability factors were found to be significantly correlated with one-another, but the nature of the correlations had changed over the course of one year. More specifically, many of the household correlations (for

example, between low income levels and living in multi-family buildings) found in the survey data from a one-year follow-up study suggest that those that were socially vulnerable at the time of the disaster became even more so, rather than recovering to a less vulnerable state.

The linear regression analysis was performed using the Lumberton dataset which consisted of 861 household and 217 business datapoints. From this analysis, two functions to predict each of household dislocation duration and business downtime duration were obtained. The explanatory variables used for the household dislocation regression model were the overall damage state of the home, the race of the household, the ownership of the home, and the number of days of work missed by the household. Interior contents damage state, days of utility loss, personal issues experienced by the employees and the relative size of the business according to Small Business Administration size standards were used for the business downtime regression model. Based on these explanatory variables, three resource types were chosen for the case study. The resource types were structural retrofits for households in the form of home elevation to above expected floodwater heights, and the installation of standby generators, elevated structural platforms, and waterproof rooms in the businesses. In addition to these retrofits, a retrofit to an existing levee system protecting southwest Lumberton was also considered.

A total of ten resource distribution strategies were considered in the case study, using different combinations of retrofit types, societal fairness principles and maximum total cost constraints. Four levels of societal fairness were used: 1) none, 2) equal distribution, 3) semi-equitable distribution, and 4) equitable distribution. Since equitable distributions were desired, the optimization portion of the SORD framework was implemented. Genetic algorithm optimization, a procedure which imitates biological evolution, was adopted and a brief overview of using genetic algorithms for optimization was provided. The implementation of a maximum cost constraint led

to a total of five equity-based optimizations being completed. Included in the five were a cost constrained and an unconstrained optimization for each of households and businesses, and one optimization for both households and businesses together. Finally, the results of the optimizations for equity were compiled with the other resource distribution strategies and compared.

5.1 Conclusions

Correlation and regression analyses were conducted as part of the Lumberton case study; the results of these analyses were valuable beyond their use in the SORD framework. The correlation analysis presented two important conclusions, within the context of the Lumberton study. First, the nature of the interplay between the studied social vulnerability factors changed considerably between November 2016 and January 2018. For example, the 'Children in Household' factor lost two significant correlations, and gained one, with other factors during that time. In another case, the 'Hispanic Household' factor was no longer significantly correlated to three other factors. Notably, however, none of the significant correlations changed from positive to negative, or vice versa.

The second conclusion from the correlation analyses was that the strength of some correlations increased drastically during the disaster recovery timeline. This is most clearly observed for the 'Multi-Family Building' and 'Renter household' factors, whose correlation coefficients with low household incomes increased by upwards of 222% in magnitude between November 2016 and January 2018. The 'Black household' and 'Minority household' factors also experienced similar results, with their significant correlations with lower household incomes becoming up to 117% stronger. These results suggest that, overall, the Lumberton households associated to these factors did not experience economic recovery over time, but rather the opposite.

The regression analyses performed for the Lumberton case study provided some valuable insight into the relative effects of some vulnerability factors on the durations of household dislocation and business downtime. In particular, Black and American Indian households were expected to experience the longest dislocation durations, on average 20.7 days and 15.5 days more than White households, respectively. Additionally, renter households in 2016 Lumberton were expected to experience 20.2 fewer days of dislocation compared to homeowner households, holding all other predictor variables constant. The effect of the social vulnerability factors, however, were generally lesser than that of overall building damage, ranging from 18.6 days with minimal damage to 192.7 days for complete destruction.

For business downtime duration, employee mental distress was found to be the most influential factor (on average 51.6 additional days if mental distress exists); this was even more than a complete destruction of the internal contents of the business's building (on average 45.6 additional days). Small businesses, as defined by the Small Business Administration's size standards, were more susceptible to longer downtime as well, with an average of 16.6 more days of downtime than larger businesses. Finally, the electric utility was found to have a much larger effect (approximately 2.5 times greater) on potential downtime duration than the other utilities considered together.

In general, the optimization results suggested not only that some level of equity was possible (reaching an average difference of household dislocation duration of 13.8 days and 16.5 days for businesses), but that the equitable resource distributions were also quite cost-effective (on average 45.8% less expensive to increase equity, compared to the equality- and semi-equity based resource distributions). Equity-based solutions also had the highest cost-effectiveness for reduction of total dislocation or downtime duration (on average 43.5% less expensive than the

other distributions), and average cost per household and business (36.7% lower on average compared to the other distributions). This was achieved in the equity solutions with only somewhat greater total durations of downtime or dislocation than their equality- or semi-equity based counterparts (on average 11.0% greater total durations).

Because only structural retrofits were considered as resources for the Lumberton case study, the possible reduction in dislocation and downtime durations was limited. The regression analysis showed that the maximum possible reduction in household dislocation duration was 192.7 days; however, the longest dislocation duration could only be reduced by 6.3% (18.6 days) because the majority of this duration was not attributed to structural damages. The longest business downtime duration was able to be reduced by the maximum possible through retrofits, 45.6 days (28.9% of the non-retrofitted downtime duration). This clearly indicates that mitigation which eliminates pre-existing social inequities will most substantially improve community resilience.

Overall, the Lumberton case study showed that the SORD framework can be applied to a real-world scenario, and the equitable resource distributions which were obtained using the framework were shown to be more desirable than equality-based distributions in terms of both societal fairness and monetary cost.

5.2 Contributions to the Field

Four major contributions have been made to the fields of civil engineering and disaster management through the research performed for this dissertation. Perhaps the most crucial contribution was the implementation of equity as the main driving factor of the research. This was done by adopting equity, and societal fairness in general, as the measure of effectiveness for disaster resource management. Based upon the literature review conducted as part the dissertation,

this research will have been one of the first instances of specifying equity as the main objective of an engineering-based disaster management framework. It is hoped that by showing that societal fairness can serve as a major decision-making factor in civil engineering framework, other works will follow suit. Similarly, a second contribution is the specifics of how equity and equality were measured in a quantitative framework, as no such established metrics or equations for equity and equality were identified in the literature.

The SORD framework produced as part of this dissertation may allow for just that to happen. The resource distribution framework presented herein provides the necessary steps for optimizing solutions based on societal factors, but is general enough to be applied to a wide variety of scenarios of varying hazards, communities and objectives. The framework may be adopted by not only other disaster resilience researchers, but by organization officials and decision makers as well to design for equitable outcomes for the communities that they serve. The case study of Lumberton, NC, provides contextual evidence and guidance towards the proper use of the framework to achieve such goals.

The two statistical analyses conducted within the Lumberton case study can also serve many purposes beyond the case study itself. First, the correlation analysis which was conducted using the Center's longitudinal study data showed that the interplay between certain social vulnerability factors can change over time, and sometimes in unexpected ways. How social vulnerability changes over time after disasters has not been measured in the literature before, and there too, is a lack of information on intersectionality of perceived social vulnerability factors. This in itself reinforced the importance of tracking recovery and the characteristics of a community over longer periods of time. The regression models for household dislocation duration and business downtime duration can also be useful within the correct contexts. It is not suggested that they are

generically useful for other communities and conditions, but they can be used for comparison and a basis for other similar models for predicting the societal damage outcomes of natural hazards.

5.3 Limitations

Several limitations restricting the research conducted here relate to the framework illustration. The most crucial of these limitations is that the case study and many of its findings are limited to the households and businesses included in the survey dataset, the community in which they inhabited, and for the circumstances surrounding the 2016 flooding caused by Hurricane Matthew. Since such detailed, granular, and longitudinal datasets are not readily available, the adoption of multiple comparative case studies was not possible. This unique combination of conditions make it implausible to extend the specific findings to any other community or hazard, though the SORD framework itself is very much broadly applicable.

Additionally, the incorporation of the case study itself was limited in scope. The majority of the focus was placed here on the households and businesses in the existing dataset and did not actively consider the interactions with this group and the remainder of the community. In addition, the case study only considered local effects, whereas a disaster scenario typically has many state- and federal level actors, and the associated access to resources. The details of which funding sources provided the resources distributed in the framework were not articulated in the framework application. Businesses do not have access to pre- or post-disaster funding, outside of high interest rate loans, and rarely do households have access to pre-disaster funding. Thus more explicit consideration of funding streams are necessary for application of the SORD framework in practice. Finally, only one particular type of resource (e.g., structural mitigation) was considered in the case study; many non-structural options are valid, and potentially more valuable, for disaster mitigation, and their particular uses and limitations should be considered.

Another important limitation exists with the current state of the SORD framework, one that had been hinted at by results from the case study itself. As suggested by the correlation analysis, and as reported by numerous studies previously, outcomes such as societal damage are time dependent. The framework currently does not explicitly address this influence of time, and this should be properly addressed in any future work referencing this dissertation.

Finally, the framework is built on societal damage metrics. As discussed in Chapter 3, these can be adopted from census data, however, the granularity and extent of variables would be greatly limited compared to what was enabled through the illustrative example that benefited from individual household- and business-level resilience and recovery-centered data collected through the Lumberton field study. Thus, a significant limitation and challenge to applying the framework more broadly is the collection of data that would meaningfully support an equity measurement in a community. Such data collection is not common practice at the local government level, and such research projects are also uncommon.

Furthermore, the illustrative example used real post-disaster data to determine the extents of the disaster impacted area. Use of the framework without post-disaster data would require the use of integrated physics-based models, including hazard simulation, building damage assessment, and subsequent impact prediction, which are not easily accessible by researchers or actual decision makers who distribute resources in practice. Moreover, such offices will not necessarily have the ability to run sophisticated regression analyses should they have access to such data. These exact dilemmas are the impetus for the NIST Center of Risk-Based Community Resilience Planning's product, IN-CORE, however it is still under development. Thus, significant advances in research and changes to practice might be required for the SORD framework to reach its full potential in influencing the equitable distribution of pre- and post-disaster resources.

5.4 Future Work

This dissertation laid down the foundation for a variety of potential work. One particular topic was just discussed in the previous section, in that the effect of time was not expressly included in the framework. Integrating time-based resource distributions into the framework can allow for the consideration of chronic hazards such as drought, coastal erosion and disease, as well as resource distributions *during* the occurrence of the hazards. Long-term resource distribution can also be designed if multiple timeframes can be considered using the SORD framework; the correlation analysis conducted as part of the Lumberton case study demonstrated how needs (based on social vulnerability) can evolve over a disaster timeline. This will be one of the primary goals for expanding the potential of the SORD framework. Furthermore, equity serves as a major cornerstone in the research conducted. However, equity was measured in one fashion in the included case study, where it was based upon an average difference of days of dislocation or downtime. This definition is fairly specific and would not be applicable for some other uses of the framework. Therefore, future work will include studies on other ways to measure or define equity, particularly for practical use in disaster management research.

Beyond these two main focuses, the framework can be further supported by determining how to model other types of resources. Additional types of resources that should be considered in a disaster setting include human resources (e.g., local organizations, workers, or manpower), information (e.g., available data, or information flow and distribution), and available time. Baseline models such as these, especially those that could be generalized to other communities, can facilitate the practical use of the framework. In line with these other types of resources, study on the use of post-disaster resources, in contrast to the pre-event retrofits considered in this dissertation, will also be ideal.

In addition to a wide variety of resources, universal models for predicting the outcomes of hazards and resource distributions would be highly convenient. Currently, the assumption stands that data-driven predictive models are unique to particular scenarios. However, perhaps with enough data, the development of generalized predictive models could be possible. These models would not only enhance the global applicability of the SORD framework but also greatly support community disaster resilience research in general.

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Appendix A. Variables used for statistical analysis

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks.

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
All	The order of the original variables listed is the order considered when compiling; Usually take Wave 2 data over Wave 1, unless Wave 2 is blank; If either are blank, take the other value; if both are blank, leave blank; 99 (don't know), 999 (no answer / refused), etc. are treated as blanks when compiling		
DepDisl	Household dislocation duration, based on Q17, disldys_assmd or dispdys_assmd	ratio	Number of days the household was dislocated
DepDisl_Log	Dependent variable - duration of household dislocation; based on Q17, disldys_assmd or dispdys_assmd 0 if less than or equal to 14 days (2 weeks) 1 if less than or equal to 61 days (2 months) 2 if less than or equal to 183 days (half-year) 3 if greater than 183 days	ordinal	Reference//DepDislR = 1 if less than or equal to 14 days
BldgArea	Building footprint area in square feet; based on Houselengthft and Housewidthft Houselengthft * Housewidthft	ratio	Building footprint area in square feet
BldgConst	Building construction material; based on Constructiontype 0 if wood 1 if masonry 2 if other (incl. wood & masonry)	nominal	Reference//BldgConstR = 1 if wood BldgConst1 = 1 if masonry BldgConst2 = 1 if other
BldgFndn	Building foundation construction material; based on Foundationtype 0 if crawlspace 1 if slab-on-grade 2 if other	nominal	Reference//BldgFndnR = 1 if crawlspace BldgFndn1 = 1 if slab-on-grade BldgFndn2 = 1 if other

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
BldgQual	Average of Maintenance and Quality; based on Maintenance and Quality 0 if low 1 if average 2 if good 3 if excellent	ordinal	Reference//BldgQualR = 1 if excellent BldgQual1 = 1 if low BldgQual2 = 1 if average BldgQual3 = 1 if good
BldgStoreys	Number of storeys in the building; based on Numberofstories If Numberofstories is blank, and if BldgType is 2 (mobile home), set as 1	ratio	Number of storeys in the building
BldgType	Type of building; based on Buildingtype or bldtyp3 0 if single-family dwelling 1 if multi-family dwelling 2 if mobile home	nominal	Reference//BldgTypeR = 1 if single-family BldgType1 = 1 if multi-family BldgType2 = 1 if mobile home
BldgUnits	Number of living units in the building; based on P1Q5_3 If P1Q5_3 is blank, and if BldgType is 0 (SFD) or 2 (MH), set as 1	ratio	Number of living units in the building
DemoEduc	Highest number of years of schooling completed by a household member; based on Q27_2, yrschool, Q27_1 or degree If using Q27_1 or degree, take HS = 12, Asc = 14, Bach = 16, Mst = 18	ratio	Highest number of years of schooling completed by a household member
DemoElder	Presence of elderly members in the household; based on age_elderhh, age_welder 0 if no elder in the household 1 if there is at least one elder in the household	binary	Reference: 0 if no elders in the household DemoElder = 1 if at least one elder in household
DemoEmply	Full-time employment in the household; based on full_empl 0 if at least one member of the household has a full-time job 1 if no household members have a full-time job	binary	Reference: 0 if at least one full-time employment DemoEmply = 1 if no members have full-time employment

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
DemoInc	Household income relative to poverty level for household size; based on Q30 or P4Q7 Determine household size using Q2_3 or P3Q1 0 if household is below poverty level (0 to 99% of poverty level) 1 if household is between 100 to 199% of poverty level 2 if household is between 200 to 299% of poverty level 3 if household is between 300 to 399% of poverty level 4 if household is at or above 400% of poverty level	ordinal	Reference//DemoIncR = 0 if household is below poverty level DemoInc1 = 1 if household is between 100 to 199% of poverty level DemoInc2 = 1 if household is between 200 to 299% of poverty level DemoInc3 = 1 if household is between 300 to 399% of poverty level DemoInc4 = 1 if household is at or above 400% of poverty level
DemoMinor	Presence of minors in the household; based on Q2_2 or age_wminor 0 if there are no minors 1 if there is at least one minor	binary	Reference: 0 if there are no minors in the household DemoMinor = 1 if there is at least one minor
DemoTenure	Building is owned or rented by the household; based on Q9 or ownrshp_assmd 0 if the household owns the building 1 if the household rents the building	binary	Reference: 0 if the building is owned by the household DemoTenure = 1 if the building is rented by the household
DemoRace	Household racial makeup; based on Q28 or P4Q5_1 0 if household is entirely white 1 if household is entirely black 2 if household is entirely American Indian 3 if other	nominal	Reference//DemoRace0 = 0 if the household is entirely white DemoRace1 = 1 if household is entirely black DemoRace2 = 1 if household is entirely American Indian DemoRace3 = 1 if household is any other (or combinations of) race
DemoEth	Household ethnical makeup; based on Q29 or P4Q6 0 if not hispanic 1 if household is hispanic	binary	Base group: 0 if household is not hispanic DemoHisp = 1 if household is hispanic

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
DemoInc	Household income relative to poverty level for household size; based on Q30 or P4Q7 Determine household size using Q2_3 or P3Q1 0 if household is below poverty level (0 to 99% of poverty level) 1 if household is between 100 to 199% of poverty level 2 if household is between 200 to 299% of poverty level 3 if household is between 300 to 399% of poverty level 4 if household is at or above 400% of poverty level	ordinal	Reference//DemoIncR = 0 if household is below poverty level DemoInc1 = 1 if household is between 100 to 199% of poverty level DemoInc2 = 1 if household is between 200 to 299% of poverty level DemoInc3 = 1 if household is between 300 to 399% of poverty level DemoInc4 = 1 if household is at or above 400% of poverty level
DemoMinor	Presence of minors in the household; based on Q2_2 or age_wminor 0 if there are no minors 1 if there is at least one minor	binary	Reference: 0 if there are no minors in the household DemoMinor = 1 if there is at least one minor
DemoTenure	Building is owned or rented by the household; based on Q9 or ownrshp_assmd 0 if the household owns the building 1 if the household rents the building	binary	Reference: 0 if the building is owned by the household DemoTenure = 1 if the building is rented by the household
DemoRace	Household racial makeup; based on Q28 or P4Q5_1 0 if household is entirely white 1 if household is entirely black 2 if household is entirely American Indian 3 if other	nominal	Reference//DemoRace0 = 0 if the household is entirely white DemoRace1 = 1 if household is entirely black DemoRace2 = 1 if household is entirely American Indian DemoRace3 = 1 if household is any other (or combinations of) race
DemoEth	Household ethnical makeup; based on Q29 or P4Q6 0 if not hispanic 1 if household is hispanic	binary	Base group: 0 if household is not hispanic DemoHisp = 1 if household is hispanic

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
DmgFlood	Floodwater elevation at the building; based on Floodlevel or HWMlocation If Floodlevel is negative, set to 0; If HWMlocation = 1 (foundation), set DmgFlood = 0 inches; If HWMlocation = 2 (1st floor), set DmgFlood = 13 (average of all Floodlevel where HWMlocation = 2)	ratio	Floodwater elevation at the building (inches above FFE)
DmgInt	Damage state of the interior of the building; based on InteriorDamage 0 if DS0 1 if DS1 2 if DS2 3 if DS3 4 if DS4	ordinal	Reference//DmgIntR = 1 if DS0 - no damage DmgInt1 = 1 if DS1 DmgInt2 = 1 if DS2 DmgInt3 = 1 if DS3 DmgInt4 = 1 if DS4
DmgOvrll	Damage state of the overall building; based on Ovrlldmg_assmd or Q8a (W1 takes precedence) 0 if DS0 1 if DS1 2 if DS2 3 if DS3 4 if DS4	ordinal	Reference//DmgOvrllR = 1 if DS0 - no damage DmgOvrll1 = 1 if DS1 DmgOvrll2 = 1 if DS2 DmgOvrll3 = 1 if DS3 DmgOvrll4 = 1 if DS4
DmgUtil	Maximum number of days of utility loss; based on P2Q#_# If P2Q#_4 = 1 (still don't have service), use max of P2Q#_3	ratio	Maximum number of days of utility loss
DmgWork	Days of work missed; based on Q19 and Q19a or msswrk_avg If Q19 = 2 (did not miss work) or 4 (N/A), set to 0	ratio	Number of days of work missed
FundInsrA	Household insurance; based on Q9a, Q9b and Q9c or P4Q2_4 and P4Q2_5 0 if household has insurance (rent, flood or homeowner's) 1 if household did not have any type of insurance	nominal	Reference: 0 if the household had insurance FundInsrA = 1 if the household did not have insurance

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
FundInsrB	Household insurance funding received; based on Q9d 0 if household received insurance payout 1 if household did not receive payout but had insurance *WARNING: UNKNOWN IF DAMAGES WERE CLAIMED*	binary	Reference: 0 if household received insurance payout FundInsrB = 1 if the household did not receive payout but had insurance *WARNING: UNKNOWN IF DAMAGES WERE CLAIMED*
FundInsrC	Delay of insurance funding disbursement; based on Q9e_1, Q9e_2 and Q9e_3	ratio	Delay of insurance funding in days if household received funds
FundInsrD	Amount of repairs covered by insurance funding, if funding received; based on Q9f 0 if none 1 if very little 2 if some 3 if almost all/all	ordinal	Reference//FundInsrCR = 1 if almost all/all FundInsrC1 = 1 if none FundInsrC2 = 1 if very little FundInsrC3 = 1 if some
FundOtherA	Application for non-insurance external funding; based on Q10_1, Q11_1, Q12_1, Q13_1, Q14_1 and Q15_1 or P4Q3_4, P4Q3_5, P4Q3_6 and P4Q3_7 0 if external support not applied 1 if external support applied	binary	Reference: 0 if external support was not sought 1 if external support was sought
FundOtherB	External support received when applied for; based on Q10_2, Q11_2, Q13_2, Q14_2, and Q15_2 0 if external support received 1 if external support not received	binary	Reference: 0 if external support was received 1 if external support was not received but was applied for
FundOtherC	Maximum delay in receiving external funding; based on Q10_3, Q11_3, Q12_3, Q13_3 and Q15_3	ratio	Maximum delay in receiving external funding in days

Table A1. Initial list of household variables, compiled using the Center's original survey data and codebooks (continued).

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
FundEnough	Amount of repairs covered by funding received from both insurance and other external sources; based on Q16 and Q16a 0 if none 1 if very little 2 if some 3 if almost all/all	ordinal	Reference//FundEnoughR = 1 if almost all/all FundEnough1 = 1 if none FundEnough2 = 1 if very little FundEnough3 = 1 if some
RecvAccess	Household's access to surrounding community; based on Q23 0 if same access was had 1 otherwise	binary	Reference: 0 if same access was had RecvAccess = 1 otherwise
RecvDelayA	Effect of funding delay on household dislocation duration 0 if not affected by funding delay 1 if dislocation duration was affected by funding delay	binary	Reference: 0 if funding delay did not affect dislocation duration RecvDelayA = 1 otherwise
RecvDelayB	Effect of workplace conditions on household dislocation duration 0 if not affected by workplace conditions 1 if dislocation duration was affected by workplace conditions	binary	Reference: 0 if workplace conditions did not affect dislocation duration RecvDelayB = 1 otherwise
RecvDelayC	Effect of school conditions on household dislocation duration 0 if not affected by school conditions 1 if dislocation duration was affected by school conditions	binary	Reference: 0 if school conditions did not affect dislocation duration RecvDelayC = 1 otherwise
RecvDelayD	Effect of business closures on household dislocation duration 0 if not affected by business closures 1 if dislocation duration was affected by business closures	binary	Reference: 0 if business closures did not affect dislocation duration RecvDelayD = 1 otherwise
RecvRep	Duration of repair to full repair If 999 (still not repaired), set to 420 days (max recorded repair duration)	ratio	Number of days taken for repairs

Table A2. Initial list of business variables, compiled using the Center's original survey data and codebooks.

VARIABLE	COMPILING RULES	TYPE	(DUMMY) VARIABLE DEFINITIONS
All	The order of the original variables listed is the order considered when compiling; If either are blank, take the other value; if both are blank, leave blank; 99 (don't know), 999 (no answer / refused), etc. are treated as blanks when compiling		
DepDwnt	Dependent variable - duration of business downtime; based on Int_days	ratio	Duration of business downtime in days
DmgBldg	Damage state of the building; based on Dmg_bldg 0 if none 1 if minor 2 if moderate 3 if severe 4 if complete	ordinal	Reference//DmgBldgR = 1 if none DmgBldg1 = 1 if minor DmgBldg2 = 1 if moderate DmgBldg3 = 1 if severe DmgBldg4 = 1 if complete
DmgCust	Customer loss experienced by the business in percent; based on Cus_per	ratio	Customer loss experienced in percent
DmgEmply	Business's employee(s) had difficulties due to personal issues; based on Em_trans, Em_dmg, Em_sch, Em_phys and Em_mental 0 if all are zero 1 if any are non-zero	binary	Reference: 0 if employees experienced no difficulties due to personal issues DmgEmply = 1 if at employees experienced difficulties due to any personal issues
DmgEmplyA	Business's employee(s) had difficulties due to transportation problems; based on Em_trans 0 if no 1 if yes	binary	Reference: 0 if employees experienced no difficulties due to transportation problems DmgEmplyA = 1 if at employees experienced difficulties due to transportation problems
DmgEmplyB	Business's employee(s) had difficulties due to personal damages; based on Em_dmg 0 if no 1 if yes	binary	Reference: 0 if employees experienced no difficulties due to personal damages DmgEmplyA = 1 if at employees experienced difficulties due to personal damages

Appendix B. Damage state criteria used in the longitudinal Lumberton study

Table B1. Overall damage state descriptions for residential structures (Deniz et al. 2020).

Damage State	Description
DS 0: None	No damage; water enters crawlspace or touches foundation (crawlspace or slab on grade). No contact to electrical or plumbing, etc. in crawlspace. No contact with floor joists. No sewer backup into living area.
DS 1: Minor	Water touches floor joists up to minor water enters house; damage to carpets, pads, baseboards, flooring. Approximately 1" in house but no drywall damage. Could have some mold on subfloor above crawlspace. Could have minor sewer backup and/or minor mold issues.
DS 2: Moderate	Water level approximately 2 feet with associated drywall damage and electrical damage, water heater and furnace and other major equipment on first floor damaged. Lower bathroom and kitchen cabinets damaged. Doors or windows may need replacement. Could have major sewer backup and /or major mold issues.
DS 3: Severe	Water level 2 feet to 8 feet; substantial drywall damage, electrical panel destroyed, bathroom/kitchen cabinets and appliances damaged; lighting fixtures on walls destroyed; ceiling lighting may be ok. Studs reusable; some may be damaged. Could have major sewer backup and/or major mold issues.
DS 4: Complete	Significant structural damage present; all drywall, appliances, cabinets etc. destroyed. Could be floated off foundation. Building must be demolished or potentially replaced.

Table B2. Building damage state descriptions for business structures (Xiao et al. 2020).

Damage State	Description
DS 0: None	No damage; No contact to electrical or plumbing, etc. in crawlspace. No contact with floor joists. No sewer backup
DS 1: Minor	Water touches floor joists up to minor water enters building; damage to carpets, pads, baseboards, flooring. Approximately 1” in the building but no drywall damage. Could have some mold in crawlspace. Could have minor sewer backup and/or minor mold issues.
DS 2: Moderate	Water level approximately 2 feet with associated drywall damage and electrical damage, water heater and other major equipment. Doors or windows may need replacement. Could have major sewer backup and /or major mold issues.
DS 3: Severe	Water level 2 feet to 8 feet; substantial drywall damage, electrical panel destroyed, office cabinets or storage racks; lighting fixtures on walls destroyed; ceiling lighting may be ok. Studs reusable; some may be damaged. Could have major sewer backup and/or major mold issues.
DS 4: Complete	Significant structural damage present; all drywall, cabinets etc. destroyed. Could be floated off foundation. Building must be demolished or potentially replaced.

Table B3. Content/inventory damage state descriptions for businesses (Xiao et al. 2020).

Damage State	**Description**	
	Physical	Virtual (Data/Information, etc.)
DS 0: None	No damage	No damage
DS 1: Minor	All reusable/usable easily once dried, with zero or slight value drop	All recoverable easily
DS 2: Moderate	About 60% reusable with drying and cleaning, and moderate value drop	About 60% recoverable
DS 3: Severe	About 30% reusable with drying and cleaning, and significant value drop	About 30% recoverable
DS 4: Complete	Non-reusable once dried and total loss	Non-recoverable

Table B4. Machinery/equipment damage state descriptions for businesses (Xiao et al. 2020).

Damage State	**Description**	
	Singular	Inter-reliant
DS 0: None	No damage	No damage
DS 1: Minor	Operational easily once dried, with zero or slight value drop	All operational easily once dried, with zero or slight value drop
DS 2: Moderate	Partially operational at 60% capacity after drying and cleaning, and replacement of parts. Moderate value drop	About 60% operational after drying and cleaning, with moderate value drop
DS 3: Severe	Partially operational at 30% capacity after drying and cleaning, and replacement of parts. Significant value drop	About 30% operational after drying and cleaning, with significant value drop
DS 4: Complete	Non-operational, full replacement is required	Non-operational, full replacement and inter-reliant operating process are required

Appendix C. Statistical *SPSS* output for the developed regression models

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.673[a]	.453	.439	67.533

a. Predictors: (Constant), DmgWork, DmgOvrll1, DemoRace2, DmgOvrll4, DemoTenure, DemoRace3, DmgOvrll3, DmgOvrll2, DemoRace1

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	2.606	6.376		.409	.683
	DemoRace1	20.739	9.326	.110	2.224	.027
	DemoRace2	15.508	12.092	.058	1.283	.201
	DemoRace3	-9.491	13.015	-.033	-.729	.466
	DmgOvrll1	18.607	8.750	.096	2.127	.034
	DmgOvrll2	132.589	11.412	.512	11.619	.000
	DmgOvrll3	119.623	17.995	.281	6.647	.000
	DmgOvrll4	192.681	28.391	.281	6.787	.000
	DemoTenure	-20.200	8.899	-.099	-2.270	.024
	DmgWork	.288	.062	.192	4.623	.000

a. Dependent Variable: RecvDisl

Listwise Means

Number of cases	RecvDisl	DemoRace 1	DemoRace 2	DemoRace 3	DmgOvrll1	DmgOvrll2	DmgOvrll3	DmgOvrll4	DemoTenure	DmgWork
341	42.38	.35	.13	.11	.31	.14	.05	.02	.26	11.77

Figure C1. A screenshot of the SPSS output describing the statistics of the household dislocation duration linear regression model.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.691[a]	.478	.443	35.076645

a. Predictors: (Constant), DmgEmplyE, DmgInt2, DmgElec, DmgInt1, DmgInt3, DemoSize2, DmgEmplyB, DmgUtilO, DmgInt4

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1.558	6.038		.258	.797
	DmgInt1	1.526	9.788	.010	.156	.876
	DmgInt2	.476	13.269	.002	.036	.971
	DmgInt3	19.488	10.584	.119	1.841	.068
	DmgInt4	45.614	7.766	.413	5.874	.000
	DemoSize2	16.637	6.023	.177	2.762	.007
	DmgElec	.439	.199	.146	2.202	.029
	DmgUtilO	.176	.042	.277	4.139	.000
	DmgEmplyB	-15.831	6.053	-.169	-2.615	.010
	DmgEmplyE	51.627	16.764	.201	3.080	.003

a. Dependent Variable: DepDwnt

Listwise Means

Number of cases	DepDwnt	DmgInt1	DmgInt2	DmgInt3	DmgInt4	DemoSize2	DmgElec	DmgUtilO	DmgEmplyB	DmgEmplyE
145	25.52845	.11	.06	.09	.23	.48	9.121	29.3934	.48	.03

Figure C2. A screenshot of the SPSS output describing the statistics of the business downtime duration linear regression model.

Appendix D. Genetic algorithm optimized case study solutions

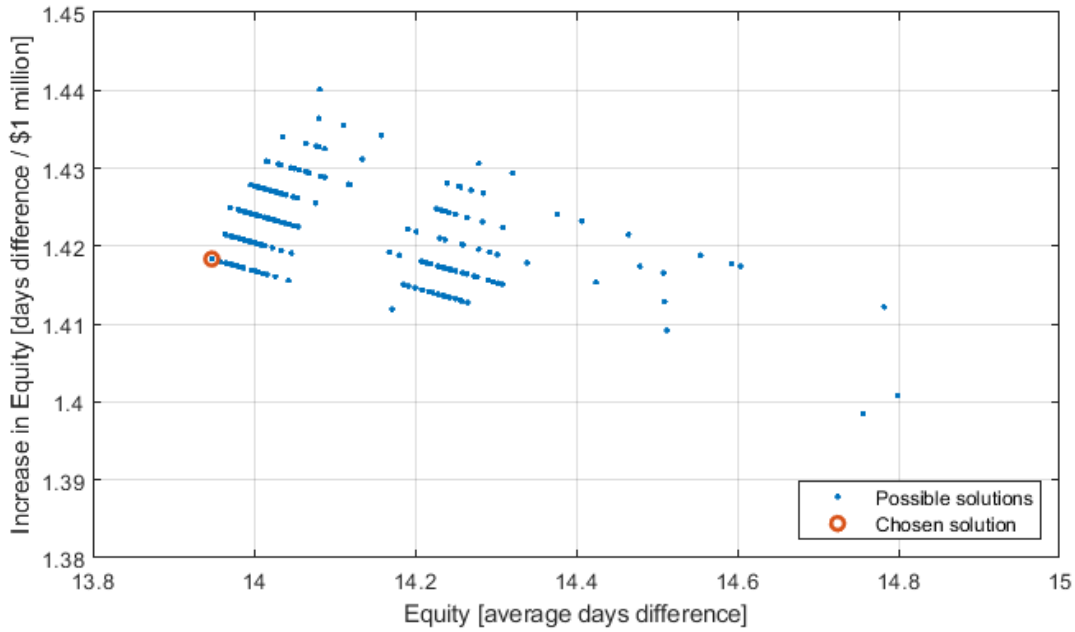

Figure D1. Genetic algorithm optimized population of resource distribution solutions for households, optimized for equity (strategy 5a). Population size = 300.

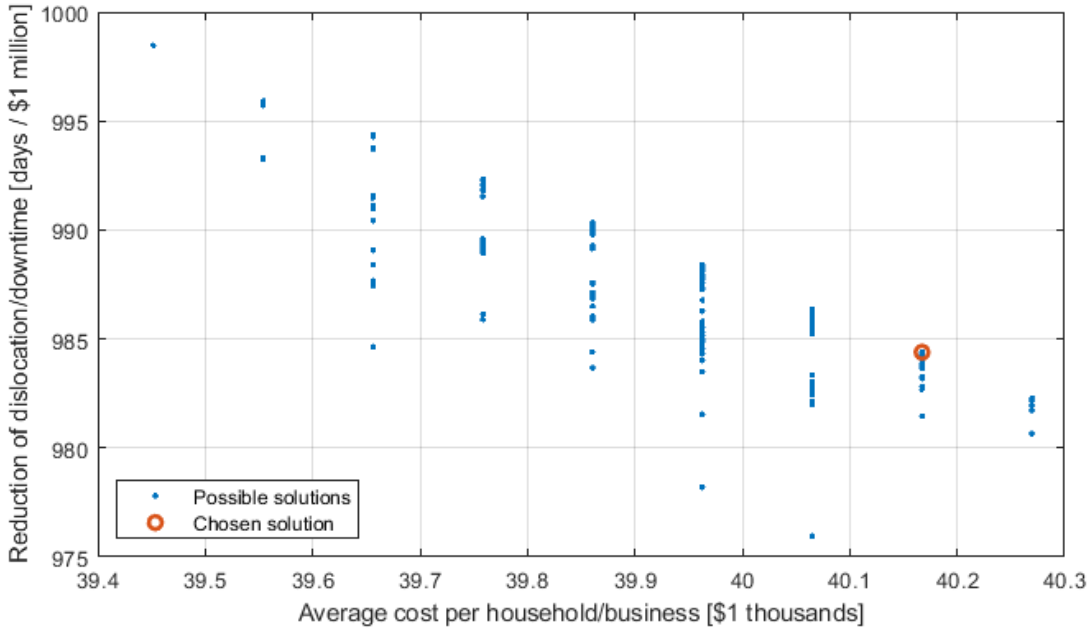

Figure D2. Average costs and reductions of total dislocation of an equity-optimized population of resource distribution solutions for households (strategy 5a). Population size = 300.

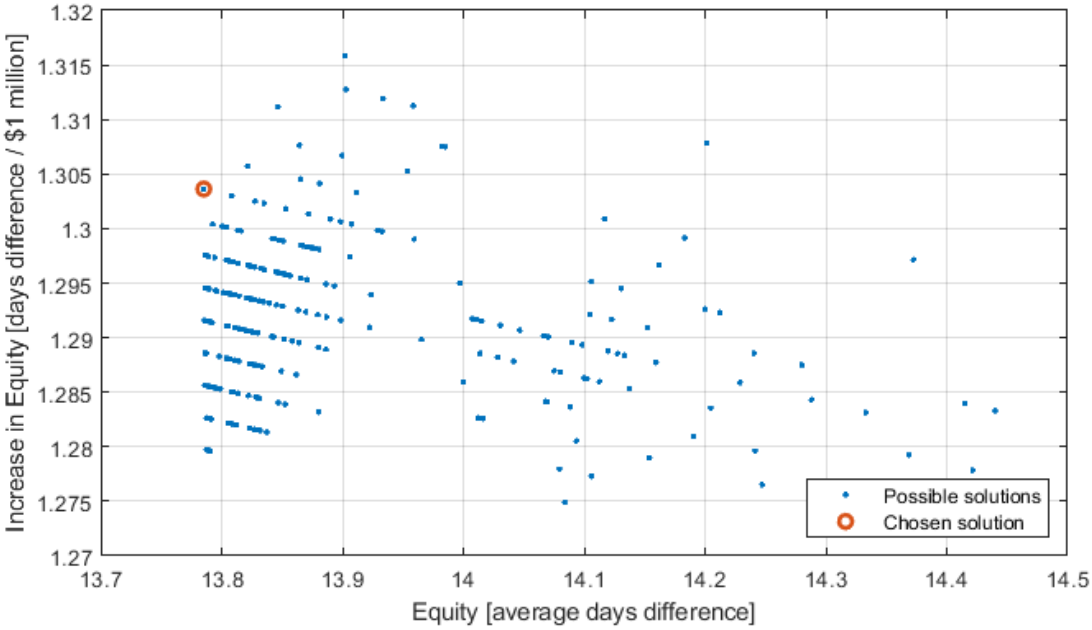

Figure D3. Genetic algorithm optimized population of resource distribution solutions for households, optimized for equity (strategy 5b). Population size = 300.

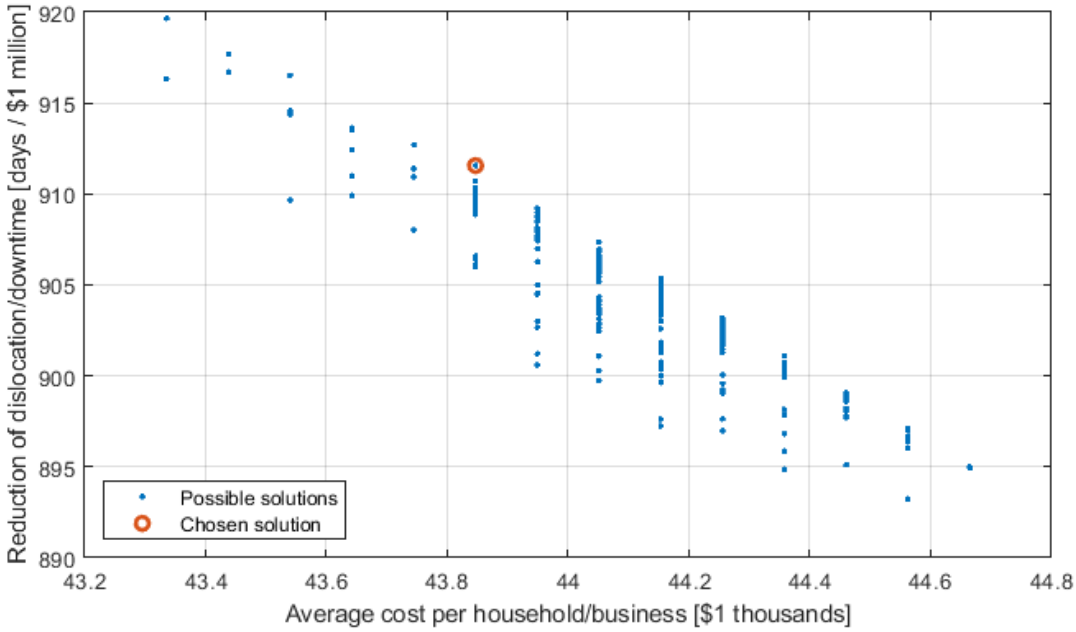

Figure D4. Average costs and reductions of total dislocation of an equity-optimized population of resource distribution solutions for households (strategy 5b). Population size = 300.

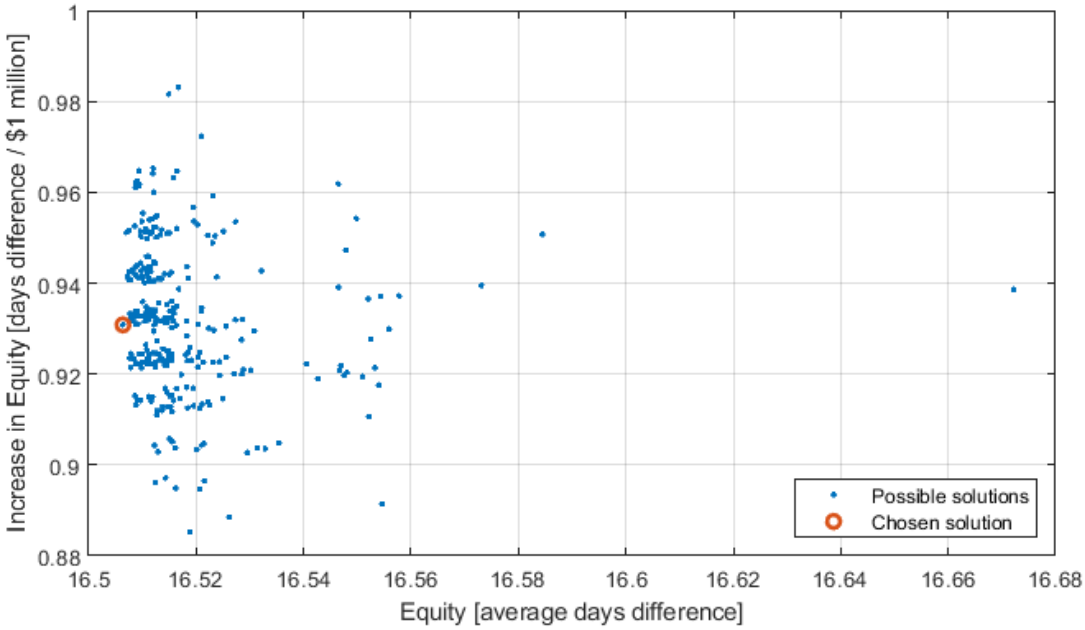

Figure D5. Genetic algorithm optimized population of resource distribution solutions for businesses, optimized for equity. Population size = 300.

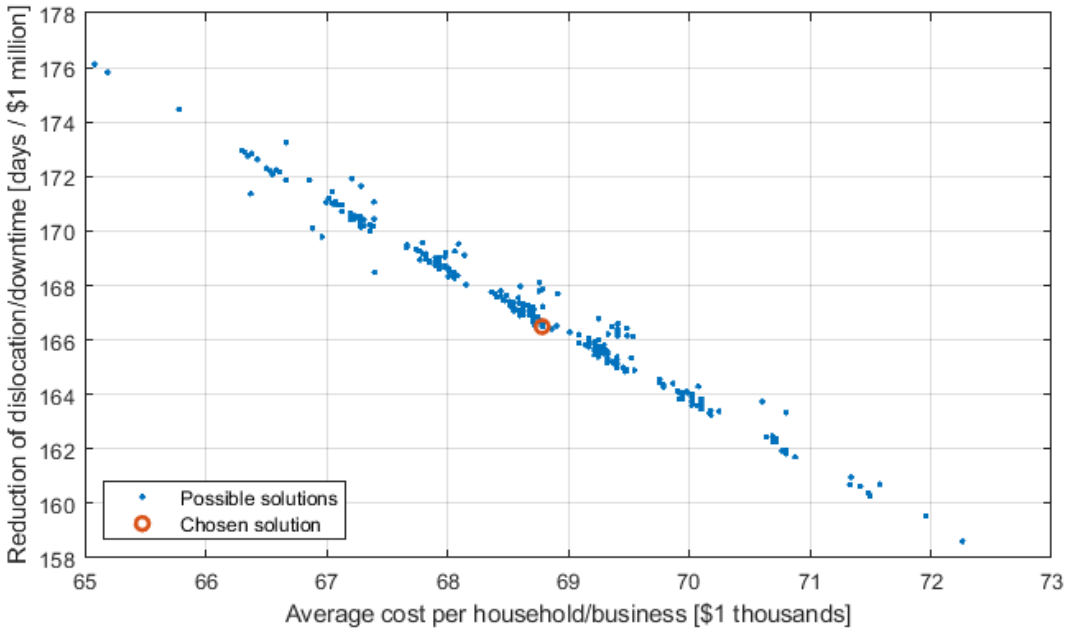

Figure D6. Average costs and reductions of total downtime of an equity-optimized population of resource distribution solutions for businesses (strategy 8). Population size = 300.

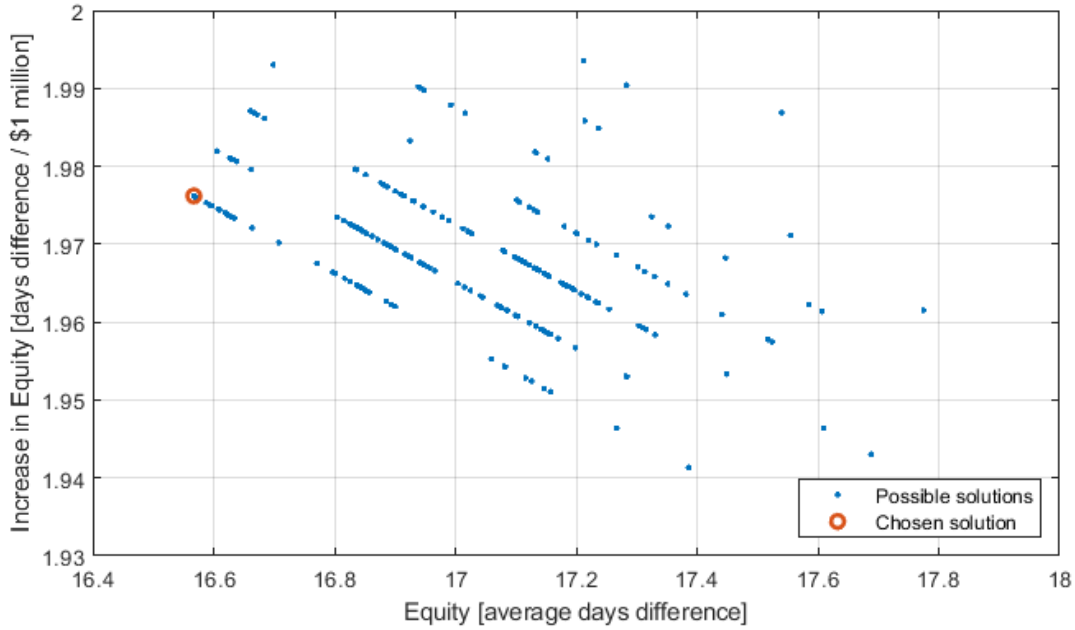

Figure D7. Genetic algorithm optimized population of resource distribution solutions for households, optimized for equal levels of household and business equity (strategy 9). Population size = 300.

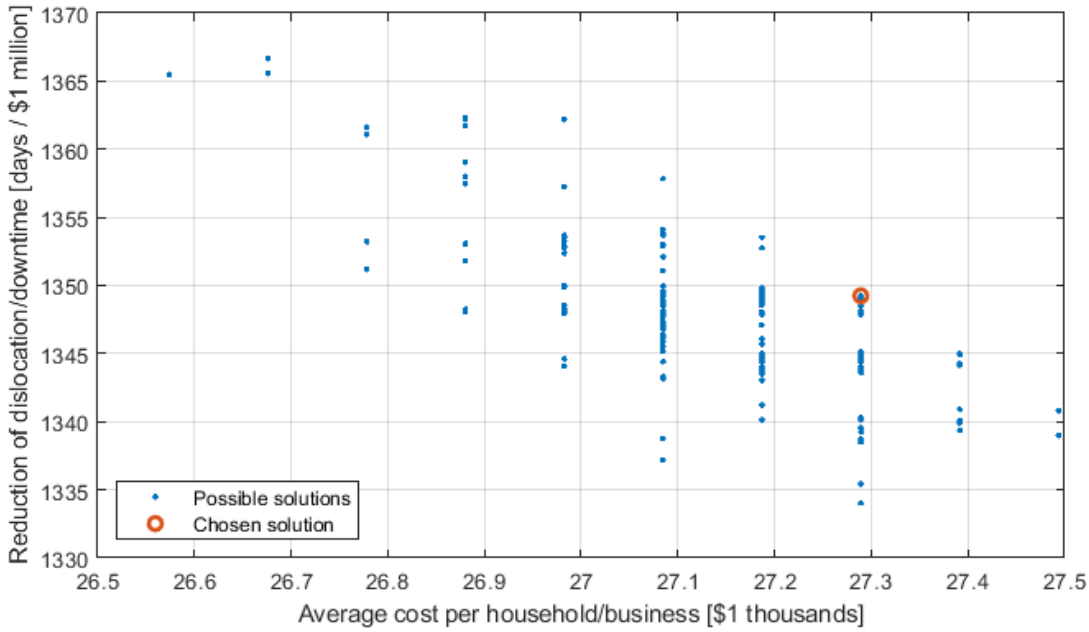

Figure D8. Average costs and reductions of total downtime of a population of resource distribution solutions for households, optimized for equal levels of household and business equity (strategy 9). Population size = 300.

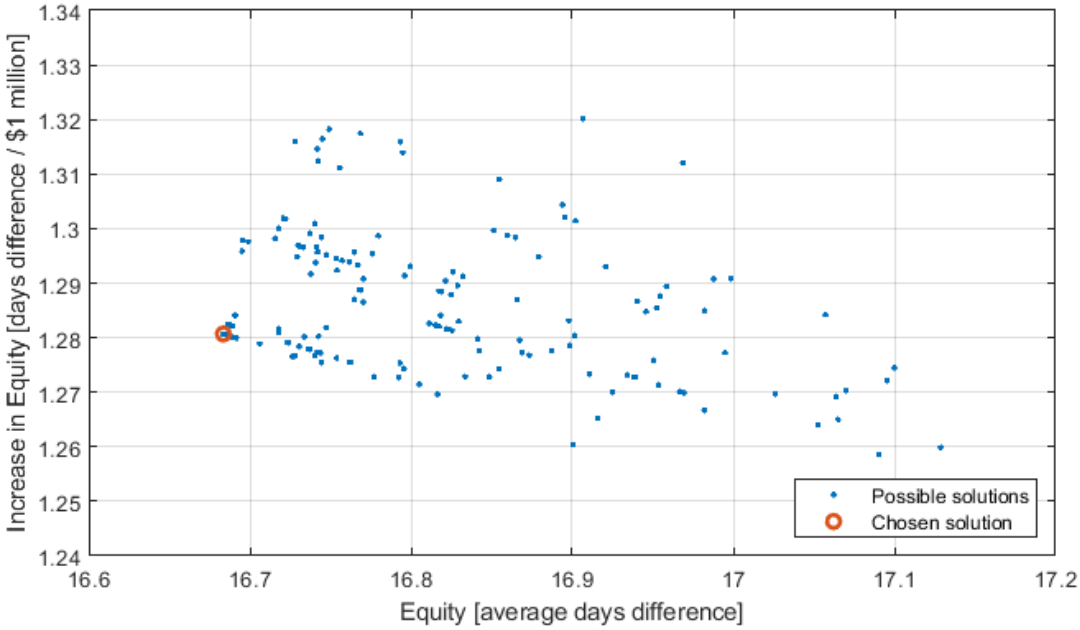

Figure D9. Genetic algorithm optimized population of resource distribution solutions for businesses, optimized for equal levels of household and business equity (strategy 9). Population size = 300.

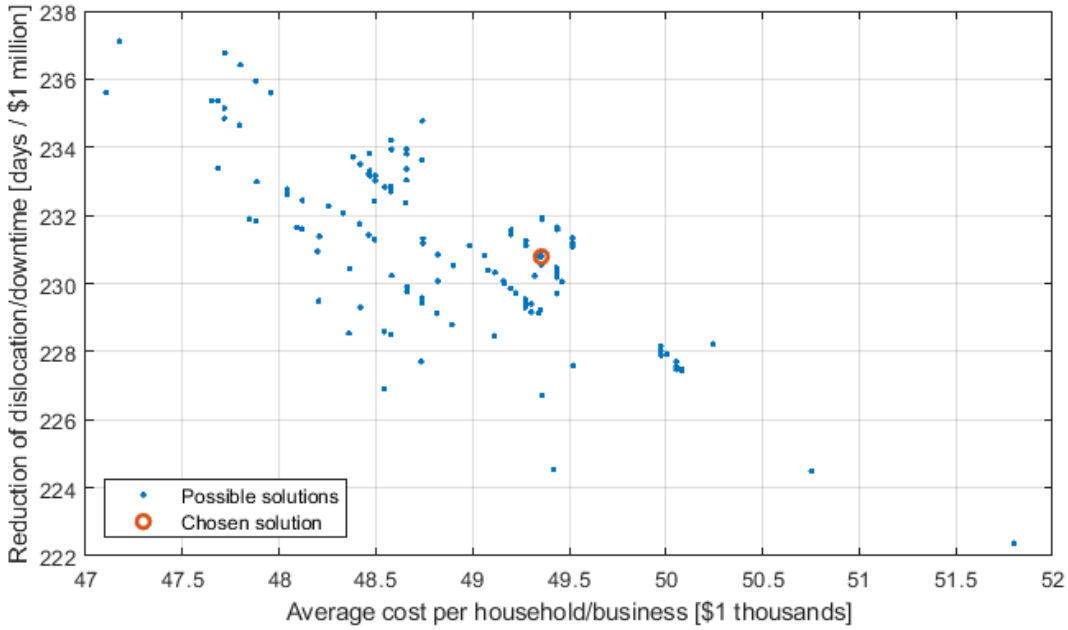

Figure D10. Average costs and reductions of total downtime of a population of resource distribution solutions for businesses, optimized for equal levels of household and business equity (strategy 9). Population size = 300.