Transitioning into Complexity-Driven Resilience Assessments for Urban Systems

by

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ABSTRACT

Extreme weather events, such as hurricanes, continue to disrupt critical infrastructure like energy grids that provide lifeline services for urban systems, thus making resilience imperative for stakeholders, infrastructure managers, and community leaders to strategize in the face of 21st-century challenges. In Puerto Rico after Hurricane Maria, for example, the energy system took over nine months to recover in parts of the island, thousands of lives were lost, and livelihoods were severely impacted. Urban systems consist of interconnected human networks and physical infrastructure, and the subsequent complexity that is increasingly difficult to make sense of toward resilience enhancing efforts. While the resilience paradigm has continued to progress among and between several disciplinary fields, such as social science and engineering, an ongoing challenge is integrating social and technical approaches for resilience research. Misaligned or siloed perspectives can lead to misinformative and inadequate strategies that undercut inherent capacities or ultimately result in maladaptive infrastructure, social hardship, and sunken investments. This dissertation contributes toward integrating the social and technical resilience domains and transitioning established disaster resilience assessments into complexity perspectives by asking the overarching question: How can a multiplicity of resilience assessments be integrated by geographic and network mapping approaches to better capture the complexity of urban systems, using Hurricane Maria in Puerto Rico as a case study? The first chapter demonstrates how social metrics can be used in a socio-technical network modeling framework for a large-scale electrical system, presents a novel framing of social hardship due to disasters, and proposes a method for developing a social hardship metric using a treatment-effect approach. A second chapter

presents a conceptual analysis of disaster resilience indicators from a complexity perspective and links socio-ecological systems resilience principles to tenets of complexity. A third chapter presents a novel methodology for integrating social complexity with performance-based metrics by leveraging distributed ethnographies and a thick mapping approach. Lastly, a concluding chapter synthesizes the previous chapters to discuss a broad framing for socio-technical resilience assessments, the role of space and place as anchors for multiple framings of a complex system, caveats given ongoing developments in Puerto Rico, and implications for collaborative resilience research.

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BACKGROUND AND INTRODUCTION

1.1 Problem Statement

Resilience, the adaptability and flexibility of systems to recover, learn, and adapt to maintain essential urban functions, has become an imperative theme for research and urban planning (e.g., National Academies, 2012; Meerow et al., 2016). In the twenty-first century, climatic disasters like heat waves and hurricanes present increasingly difficult challenges for urban systems, defined as the interconnected human networks and physical infrastructure that support essential urban functions. Infrastructure is expected to bear the brunt of impacts from disasters, but at the same time, efforts have also acknowledged the need to enhance the resilience of communities and individuals in the face of infrastructure failures and social vulnerabilities (Abramson et al., 2015). The inevitability of impacts (i.e., vulnerability) to urban systems from disasters is becoming increasingly acknowledged (Anderies et al., 2016; Engle, 2011).

In the Anthropocene, the age where technology and social systems have evolved to a scale where humans and technology have a disproportionate impact on and terraform the Earth System, the dynamics triggered by climatic disasters occur in an age of accelerating change, complexity, and unpredictability (Allenby, 2013; Crutzen, 2006; Milly et al., 2008). Such a future is characterized by complex adaptive systems (CAS), which are systems made up of interconnected networks with many interacting heterogeneous components that produce synergistic effects and emergent phenomena that are difficult (or impossible) to predict (Turner & Baker, 2019). The complexity paradigm often takes on contrasting assumptions to traditionally embraced Newtonian assumptions for scientific research, which are still practiced (Cilliers et al., 2002; Heylighen et al., 2006). Complexity sciences tend to focus on unearthing the dynamics between variables and leveraging ways to "nudge" systems toward desirable states, rather than primarily developing predictive models and solutions that reduce risks or harden infrastructure against known and foreseen stressors and shocks.

The objective of this dissertation is to address the remaining challenges toward integrating complexity perspectives into established disaster research and transitioning into systems thinking strategies for resilience assessments. In turn, such an effort can aid in activating and enhancing resilience capacities in the face of future disasters. Resilience assessment methodologies still do not acknowledge the growing complexity of urban systems, and when they do, they tend to annex additional variables of urban sub-systems rather than focus on key properties and dynamics between sub-systems. Current approaches to resilience research and practice rely largely on traditional approaches that assume stationarity (i.e., future parameters will vary within a historical envelope), or otherwise rely on approaches that reduce complexity to simple sets of variables and predictive models based on historical data (Chester & Allenby, 2019; Milly et al., 2008). On the other hand, some methods such as composite resilience indices are adopting increasingly larger sets of variables while missing the relationships between them and between the sub-subsystems they are a part of (e.g., interactions between institutions, and between social systems and ecological systems).

Resilience emerges from CAS, yet cities are not yet equipped with concepts, frameworks, and tools that sufficiently match-up this complexity, which can lead to maladaptation, mounting social and economic costs, and reduce the flexibility and agility of urban systems to adapt (i.e., lock-in) to unforeseen events (Allenby, 2012; Cilliers et al., 2013; Naughton, 2017). Strategies based on insufficient conceptualization and operationalization of resilience measures can trade-off flexibility in coupled infrastructure systems (coupled physical systems like power and water, and the institutions that design and govern them) in an era of increasing socio-technical complexity and unpredictability. In turn, investments toward enhancing resilience and adaptive capacities of urban systems can result in maladaptive strategies and investments in assets that do not payoff, ultimately undercutting the resilience of cities and well-being of communities. However, methods that embody the analysis of deep and constantly evolving information regarding such systems, which are characterized by constant flux and include sociocultural dynamics that are beyond objective observation and measurement (i.e., “thingness”), are still needed.

Essential dynamics and trade-offs between the domains of urban systems (i.e., social, ecological, technical) need to be understood, and key processes can be leveraged to mitigate vulnerability and enhance resilience. Although any characterization of a complex system is inherently incomplete, toward sufficiently illuminating urban dynamics, it is necessary to incorporate multiple perspectives and transdisciplinary approaches (Allenby, 2012; Cilliers, 2002). For instance, understanding the behavior of technical systems along with their manifestations in the lived experience of disaster survivors, or how social and ecological capital can cover the lack of or delayed recovery of infrastructure services can help infrastructure managers and urban planners better design and deploy mitigative technologies (e.g., distributed energy generation) or coordinate with communities when supporting community resilience initiatives (e.g., preparedness programs). Complexity-oriented resilience assessments can help identify where existing adaptive capacities can be leveraged, which trade-offs may be at play for specific resilience strategies, and lead to enhanced flexibility of urban systems to cope with an accelerating future.

1.2 Urban Infrastructure and Disaster Resilience Assessment Approaches

As extreme events like heat waves and hurricanes continue to occur, the need to develop and implement resilience strategies for urban systems remains imperative (Goldsmith & Crawford, 2014; Meerow & Mitchell, 2017; Preston et al., 2011; National Academies Press, 2012). Cities are urban systems, of which infrastructure are a part of. Infrastructure plays a key role in bearing the brunt of impacts, and adapting urban systems during and after disruptions. For example, after Hurricane Maria hit Puerto Rico, critical infrastructure were decimated, and excess deaths estimated to be 4,600 due to, at least in part, to the loss of infrastructure services like energy, which took over 8 months to recover in parts of the island (Kishore et al., 2018; Roman et al, 2019). Currently unfolding global changes, including climate change, are expected to accelerate the unpredictability and cascading extent of future disasters (Arbesman, 2016; Biggs et al., 2015). It is thus important for urban systems to develop the knowledge and infrastructure capacities necessary to adapt against rapid changes in demand, supply, and unforeseen disruptive events.

Urban systems can be generally conceptualized as the interconnected institutions (i.e., governance), networked material and energy flows, urban infrastructure and form (e.g., utilities, buildings, transportation), and socioeconomic dynamics that interact spatiotemporally (Dicken, 2011; Meerow et al., 2016). Infrastructure are the socio-technical networks of urban systems that provide essential services to cities and communities, such as water, energy, and communications, but also lay the foundation for the evolution of cities as a complex system, and therefore, play a significant part in their ability to be flexible and agile in the face of future disasters and unexpected shocks (Allenby & Chester, 2018; Anderies, 2014; Bettencourt, 2010; 2013). Coupled Infrastructure systems (CIS) are interacting combinations of multiple classes of infrastructure (e.g., institutions, natural and built infrastructure) that produce emergent outcomes over time and space (Anderies et al., 2016). In other words, CIS are composed of both networks of physical components (i.e., hard infrastructure) and the organizational arrangements and institutions that design, govern, and maintain physical systems (i.e., soft infrastructure).

Although the role of infrastructure failures and improvements are often highlighted after disasters, it has been recognized that it is also important to account for social, economic, political, and ecological dimensions that contribute to the overall resilience of urban systems (Eakin, 2017; NAP, 2012). The complexity in the coupling of these interrelated domains, let alone the complexity of social systems in as-of themselves, have presented challenges for comprehensive resilience assessments (Koliou et al., 2019). Domains that rely on either subjective data, methods, or take descriptive approaches to complex human dynamics have been the most challenging to incorporate into resilience assessments that leverage performance-based methods, such as geospatial analysis, engineering approaches, and mathematical models. Still, there is a need to develop theoretical frameworks and methods to assess the resilience of urban systems toward informing urban planners, infrastructure managers and engineers, stakeholders, and communities toward preparing for future challenges.

Resilience assessments, such as those based on indicators associated with resilience capacities, enable the research and tools that can be leveraged to invest, design, and manage infrastructure facing such rapidly changing conditions and unexpected disasters (NAP, 2012). Framing and reducing the complexity of urban systems to a set of comparative metrics are attractive to urban science researchers and planners by providing clear, actionable insights toward identifying enhancements for resilience capacities (Cutter, 2016a; Preston et al, 2011). Resilience assessments have largely taken shape in the form of subjective (e.g., structure-based indicators like Cutter et al., 2010) and performance-based approaches that rely on computational models (Reddy, 2020). Assessments can focus on technical, institutional, socioeconomic, ecological, or combinations of resilience dimensions as it relates to infrastructure systems, and leverage both quantitative and qualitative methods to incorporate social considerations.

Qualitative resilience assessments involve largely subjective methods or experiential data. This can include mapping the individual narratives of different types of actors, communities, or stakeholders to resilience capacities (Borie et al., 2019; Kawano et al., 2016; Peek et al., 2020), expert elicitation (USAID), surveys and ethnographic methods (e.g., Kawano et al, 2006; Gotham & Campanella, 2013), and workshop-based approaches like the Delphi method (Bozza et al., 2015). Such methods can take advantage of local knowledge of systems and contexts can be effective toward elucidating local dynamics that are difficult to measure, such as those in the human domain like perceptions of risk and cultural histories that can be at play before, during, and after disasters.

Quantitative assessments can involve performance-based methods (such as those used via statistical or mathematical models) or metrics derived from publicly available data used as indicators. Computational models can take network approaches to determine points of criticality (i.e., critically vulnerable nodes; e.g., Vugrin & Turnquist, 2012). Dynamical approaches can model interactions that tip the system toward transition to a different state that can be either a desired or an undesired one (Miller & Page, 2007; Thurner et al., 2018). Macro-level network metrics can also be developed, such as a high-level metric for self-organization (e.g., King & Peterson, 2018). Such sophisticated modeling approaches require extensive knowledge, technical capacities and resources, and rigor, which can make them less accessible or appealing to multi-stakeholder projects (Schianetz & Kavanagh, 2008). Indicators and index approaches, however, are more accessible and offer clear measures that pertain to variables and resources relevant to planners and stakeholders (Butler, 1999; Zandt et al., 2012).

Development of resilience indicators, such as those that are geospatially explicit and composited into indices, remains a very popular resilience assessment methodology because such methods are readily reproduced, leverage publicly available data, and are amenable to be incorporated into computational models and planning tools (Beccari , 2016; Bozza et al., 2015; Karakoc et al., 2019; NAP, 2012). For example, the Baseline Resilience Index for Communities (BRIC) and Climate Disaster Resilience Index (CDRI), which largely evolved from preceding disaster risk approaches for developing a Social Vulnerability Index (SoVI), have been adopted or adapted for several use-cases (e.g., Yoon et al., 2016). Bozza et al (2015) propose a Hybrid Physical-Social Network model (HPSN) that integrates a social vulnerability index into a neighborhood-level network that includes buildings and transportation networks. Indices can also be coupled with qualitative methods, such as ethnographies, which can add nuance and illustrate how indicators manifest in the experiences of community members, which can either confirm, deny, or add nuance to quantitative assumptions (e.g., Gotham and Campanella 2013; Kawano et al. 2016; Rickless et al. 2020).

While indicator-based methods and demand for actionable metrics remain widespread, there are several limitations and contested assumptions that need to be addressed. One of the most persistent and common critiques is the lack of sufficient validation of methodologies (e.g., internal and external validation; confirmation with alternative methods; testing and ground truthing) and resilience outcomes based on indicator methods (Beccari, 2016). Another issue with resilience assessments are the absent or insufficiently captured dynamics between system components (i.e., self-organization between affected communities) or between subsystems within urban systems (e.g., social and technical; Eakin et al., 2018; Koliou et al., 2019). Most indicator approaches provide a momentary snapshot of a continuously evolving urban system, while systems thinking assumes unpredictability and a system under continuous flux (Cilliers et al., 2013). That is, the nature of urban systems from a CAS perspective challenges the generalization and application of index methods (Rus et al., 2018). As disaster research has continued to emphasize the need to observe the interdependencies and dynamics among subsystems (i.e., social, ecological, and technological dimensions of an urban system), resilience indicator methods have become increasingly comprehensive. The range of approaches and variety of variables across domains suggests that index development faces overwhelming complexity toward assessing urban systems, but not necessarily a thorough understanding and integration of fundamental CAS concepts and principles.

An effective index should focus on a well-selected set of key variables that indicate changes and key capacities in urban resilience (Rus et al., 2018), but prevailing methodologies have been annexing dimensions of urban systems (e.g., ecological and institutional) largely by way of traditional sociological (Olsson et al., 2015) and data-driven approaches, leading to evermore variables within resilience dimensions emerge as relevant. In turn, indicator development is becoming increasingly complicated by adding more variables and sophisticated methods in attempting to capture complexity. This is problematic for two reasons. A greater number of variables increases the potential degree of uncertainty, inherent assumptions for a greater number of potential dynamics, and makes validation of composite indices more difficult. More importantly, it is problematic because complexity in urban systems then appears to be interpreted and operationalized as simply many components in many different domains.

Complexity sciences tend to focus on unearthing system dynamics, while indicator-based resilience assessments aim to reduce urban resilience to a set of capitals and capacities for an overall measurement of resilience. It can be argued that composite indices are categorically misaligned with CAS theory due to the framing of resilience in an urban system as representable by a sum of its quantified parts, whereas complexity assumes synergistic effects between many autonomous interacting parts, which can be unpredictable. Composite index methodologies implicitly assume a “simple” system in that a selection of quantifiable subsystems corresponds meaningfully to how an urban system behaves. This misalignment occurs methodologically when indicators are added up and assumed to indicate some ordinal level of resilience, but also conceptually when variables are assumed to be meaningful, consistent, and generalizable from one event to another, and among different urban systems.

If complexity principles are not properly captured or implemented, research and development toward resilience assessments can be misguided toward increasingly sophisticated methods while conceptually missing the mark, resulting in inaccurate assumptions about what makes urban systems resilient. Practices such as adaptation strategies based on such assessments may not pay off and the case for investing in resilience may be undermined if resilience capacities are ill-understood, undercut, or if unintended trade-offs create new threats or vulnerabilities for communities that are a part of urban systems. Despite the practicality of resilience indices, the reduction of an urban system to a set of quantitative indicators runs the risk of sunken investments and maladaptation that can compromise the resilience of future cities (Barnett et al., 2008; Magnan et al., 2016).

This misalignment is especially important because Earth systems, such as technology and climate, are continuing to evolve, while becoming increasingly interdependent (Heylighen et al., 2006). From a CAS perspective, urban systems are characterized by interactive networks where a change in one component can affect changes in other components such that structures, organization, and other phenomena like resilience emerge in ways that cannot be explained by analyzing individual components (i.e., the sum is greater than its parts). However, while there are arguments that the use of composite indicators, resilience maps, and other types of quantitative resilience assessments are problematic, there is still demand for comparative metrics to steer adaptive strategies for urban systems (Butler, 1999; Eakin et al., 2018). Whether these metrics are useful comes down to not just the theoretical grounds and state of the art, but how they are in-turn understood and applied. Therefore, it is important for modelers and practitioners alike to understand the assumptions and limitations for the use of resilience indices.

Validating variables and methodologies, and integrating urban dynamics into resilience assessments remain key challenges, but there may be solutions by way of explicitly defining complexity concepts and frameworks with disaster resilience research, converging resilience literature between disparate disciplines, and collaborative interdisciplinary research. Efforts to push resilience assessment research and development forward can consider validation and/or confirmation of frameworks, methods, and variables from multiple perspectives. This can be done by way of stakeholder engagement and co-production, cross-referenced case studies (e.g., Rickless et al, 2020), and coupling interdisciplinary and transdisciplinary approaches. Further research can clarify the validity and usefulness of proxies for systemic properties, such as the overall ability of an urban system to self-organize, toward indicating some type of general resilience. Methods like thick mapping, spatial ethnographies, and other mixed methods that combine quantitative and qualitative data show potential avenues for furthering innovative approaches for resilience assessment. Research and development in these areas, as well as network-based computational approaches, can add nuance to established assessment approaches, recognize important exceptions and limitations to indicators, and enable novel tools for practitioners to determine how to harness adaptive capacities in the face of future disasters

1.3 Definitions and Current Status of Urban Resilience Theory

Resilience is a term that has many definitions ranging in disciplines from the physical sciences to psychology (Alexander, 2013), but in the domain of urban disaster resilience, the term has come to generally mean the ability to anticipate, withstand, and adapt to maintain systems functions and essential characteristics, or to transform if necessary (Meerow et al., 2016). Resilience differs from vulnerability in that it is focused on the ability to bounce back and learn from inevitable disaster impacts, which a city, community, or infrastructure system is inherently, despite differentially, vulnerable to. From a CAS perspective, resilience is an emergent property (outcomes borne from the interaction of many agents or components) and is observed upon perturbations, where the properties of complexity come into play in describing the qualities that sustain adaptation (e.g., self-organization). There are many parallel and sometimes linked branches in the evolution of complex systems theories (Castellani, 2014), and subsequently, many definitions and framings of CAS. Generally, CAS are networks of interacting components that individually do not produce greater understanding of the behavior of the "whole system", but interact to produce synergistic outcomes and observable properties over time and space (e.g., such as resilience) (Miller, 2007; Miller & Page, 2007). While differences occur between disciplines at the theoretical level, there are some common and generally accepted properties of complex adaptive systems. For example, Turner and Baker (2019) highlight a set of essential "tenets" based on a review of complexity theory (path dependence, non-linearity, emergence, irreducibility, adaptivity, systems have a history, systems operate between order and chaos, and self-organizing behavior).

A turn toward complexity has been observed in several research fields concerned with urban resilience to climatic disasters, such as disaster risk reduction, urban geography, and resilience engineering, and in turn, remolding the framing urban systems like cities (Allenby & Chester, 2018; Castellani, 2014; Cutter, 2016a; Folke, 2006; Holnagel, Woods, and Leveson, 2006; Meerow & Newell, 2016; Reddy, 2020). For the disaster resilience research domain, seminal publications in the field of ecology were a major influence. Namely, the resilience of ecological systems framework by Holling (1973; 2001) guided many of complexity-related concepts and frameworks adopted and developed in the disaster resilience field. Resilience in ecological systems is framed as an emergent property of socio-ecological systems (SES) composed of many interacting biophysical individuals, communities, institutions, and resource systems, which as an interconnected whole, absorb change and reorganize to maintain essential functions and an essential identity (Anderies, 2014; Walker et al., 2004). Commonly referenced principles associated with resilience of SESs include diversity and redundancy, connectivity, polycentricity, slow variables and feedbacks, understanding of CAS, learning and participation (Biggs et al., 2012, 2015; Folke et al., 2016; Wiese, 2016).

SES perspectives are traditionally more focused on ecosystems and society, but the field has extended toward the built environment, integrating coupled infrastructure systems with socio-ecological systems (Anderies, 2014; Markolf et al., 2018; Suarez et al., 2019). Urban systems then share many qualities (despite in different proportions or manifestations) as ecological systems composed of interconnected, complex and heterogeneous structures and substructures, which evolve through cycles of disturbance and adaptation (Janssen, 2001; Pandit et al., 2017). These perspectives enable the interrelation between urban infrastructure, social dynamics, ecological interactions, and technological evolution as entangled in a complex system.

Concepts related to absorbing change and coping with inevitable stresses and perturbations to maintain an essential system identity has been adapted from ecological contexts to the built environment and subsequent frameworks that are more technically oriented (Anderies, 2014; Markolf et al., 2018; Pelling & High, 2005). For engineering, resilience has represented an on-going paradigmatic turn from risk-based perspectives aiming to reduce system errors and assuming stability when disasters are absent (i.e., system safety), toward a paradigm of adaptation in coping with complexity and imperfect system knowledge (Hollnagel, Woods, and Leveson, 2006). Resilience has generally been characterized as (1) the flexibility and agility to adapt in the face of non-stationarity (Chester & Allenby, 2018), (2) the ability of critical systems to cope with and quickly recover (i.e., *robustness* and *rebounding*) from short-lived external shocks (Comes & de Walle, 2014; Hollnagel, Woods, and Leveson, 2006; Reddy, 2020; Woods, 2015), and the ability to "gracefully" extend services and functions or sustain adaptability over time (Woods, 2015). From a techno-centric point of view, Reddy (2020) suggested that resilience can be assessed in terms of five sub-attributes (Table 1.1), some of which, like robustness, relate conceptually to vulnerability and sensitivity (i.e., the inverse of robustness). Meanwhile, other engineering perspectives have recently been highlighting the need for infrastructure competencies that support the flexibility, agility, and persistence of a CAS (i.e., more closely related to the last three of Reddy's sub-attributes; restructurability, adaptivity, rebounding), assuming that urban systems are inherently vulnerable to disruptions, in the Anthropocene (Allenby and Chester, 2019; Anderies, 2014; Chester and Allenby, 2019).

Table 1.1. Reddy's (2020) sub-attributes of resilience from a techno-centric perspective.

Resilience Sub-Attribute	**Definition**
Preparedness	The ability to anticipate and proactively invest in adaptation strategies.
Robustness	The ability to withstand sudden shocks and provide the service it has been designed for.
Restructurability	The flexibility to reorganize to maintain at least partial functioning.
Restorativity (rebounding)	The ability to recover functions in a timely manner and without excessive losses.
Adaptivity	The ability to learn from failure and adversity and to incorporate changes that improve the ability of systems to handle similar events in the future.

Since many theoretical frameworks for CAS arise out of non-agent or socially agnostic systems, the role of human elements are often overlooked or downplayed (e.g., institutional structure, leadership). Conversely, the social Sciences and socio-technical research have recently been emphasizing the asymmetrical complexity of coupled infrastructure systems toward human systems in light of human capacities for cognition, social complexity, and driving Earth Systems (Allenby & Sarewitz, 2012; Manuel-Navarrete, 2015; Olsson, 2015). Human capacities make coupled systems disproportionately influenced (or dominated) by the collective choices and sociopolitical forces that govern how urban systems evolve (Allenby & Sarewitz, 2012; Manuel-Navarrete, 2015). Human agency, conscience, and societal values introduce subjective interactions into urban systems that effect emergent outcomes and system evolution.

Sociocultural systems are driven by the subjective meanings, identities, beliefs, and values that drive social and political dynamics that govern urban systems, where governance refers to, “all processes of governing whether undertaken by a government or market, or network, whether over a family, tribe, formal or informal organization, or territory, and whether through laws, norms, power, or language” (Bevir, 2012). Eakin and colleagues (2017) argue for the complexities of sociopolitical infrastructure such as formal and informal rules as necessary for urban resilience thinking. The influence of networked social factors like roles, institutions, and mental models (i.e., sociopolitical infrastructure) are at least proportional to that of physical infrastructure in affecting resilience and vulnerability dynamics (Eakin et al., 2017).

This asymmetrical weight of human systems generally seems to align with Anthropocene perspectives that increasingly underscore the irreducible complexity of social dynamics in respect to ecological and technical systems. The role of engineered systems (i.e., technology) as intricately tied to social dynamics has been described by Allenby and Sarewitz (2011), where technology has three levels of complexity (systemic, system of systems, and transformative Earth Systems) as technical components become increasingly integrated and interconnected into socio-technical (i.e., techno-human) networks of information and sociocultural systems. Infrastructure are embedded in rapidly coevolving human-technical systems due for accelerating change and high levels of unpredictability (Allenby & Chester, 2018; Chester & Allenby, 2019; Markolf et al., 2018). Engineered systems in the Anthropocene face deep uncertainty and wicked challenges, where the likelihood of various possible futures are too difficult to predict, and unexampled events require fundamentally new approaches to how we function (Allenby & Chester, 2018; Chester & Allenby, 2019; Haasnoot et al., 2013; Hallegatte, 2012; Walker et al., 2013). In turn, any conceptualization of an urban system (as a CAS) is necessarily incomplete and highly uncertain in the long-term (Allenby, 2012; Cilliers, 2013).

The challenge for disaster resilience is conceptualizing and integrating what was traditionally thought of as natural disasters into a highly interconnected and unpredictable, yet human-driven Earth system. Historically focused on emergency response and recovery, disaster research turned to a focus on risk and vulnerability, and then transitioned toward interdisciplinary approaches and resilience thinking that are beginning to cross over into the complexity sciences (NAP, 2006; 2012). In doing so, the respective research domain is moving toward increasingly comprehensive social considerations, and complexity in general. In evaluating the contribution of social sciences and to disaster research, The National Academies (2006) highlights four human dimensions for disasters including psychological, demographic, economic, and political dimensions. Currently, disaster research largely incorporates social science and the social dimension in terms of resilience capacities, such as social capital (resources and capacities enables by social networks), self-organization (often in terms of collective action), and adaptive capacity. In any case, the call for the inclusion of highly complex social considerations characterizes the "cutting edge" in how urban resilience theory and practice is developing.

While the interdependence between systems in multiple resilience dimensions has been suggesting a convergence between disciplines, there are several challenges for integrative research. Critical assumptions and methodological approaches between disaster risk approaches and CAS-oriented methods may be fundamentally different, although it is possible that indicator-based methods can be leveraged as a way to transition between dynamic models and linear indicator approaches (Schianetz & Kavanagh, 2008). Olsson and colleagues (2015) challenge the commensurability of ecological resilience frameworks with social domains, largely due to ontological differences in defining systems and the now controversial basis for social dimensions of SES frameworks coming from relatively early sociological perspectives inspired by natural sciences. Modern social science, and to a lesser degree, SES perspectives critique technical resilience approaches (such as those in the engineering domain) for narrowly focusing on the stability and recovery of technical systems, while overlooking the importance of sociopolitical dynamics, hampering transformative change or equitable transitions, and introducing trade-offs that can induce new vulnerabilities (Barrett & Swallow, 2006; Béné et al., 2014; Eakin et al., 2016; Folke et al., 2010; Tellman et al., 2018; Xu, Marinova, & Guo, 2015). These challenges, along with the trend toward integrating multiple dimensions of systems between the various disciplines participating in resilience research, are indicative of the increasingly high degree of complexity to be observed and made sense of in terms of urban systems and infrastructure going into the future, making resilience to disasters difficult to measure, manage, and predict (Jabareen, 2013).

Urban resilience seems to be converging around complexity, but established theoretical frameworks and methods for understanding urban system challenges to prepare for a future that includes pressing challenges like climate change remain insufficient (Ahern, 2011; Biggs et al., 2015; Cote & Nightingale, 2012; Folke et al., 2010; Walker & Salt, 2012; Xu et al., 2015). Interdisciplinary research, specifically, those integrating engineering and social science approaches for disaster resilience, are relevant to tackle this problem. A continued challenge is to synthesize and converge disparate disciplinary perspectives into cohesive and impactful developments of knowledge and practices to improve the capacities of cities to face future disasters in the Anthropocene – the epoch characterized by accelerating change and uncertainty predicated on the dominance of human systems. In particular, the comprehensive integration of subjective (i.e., experiential data) and performance-based approaches for resilience assessment remains an objective that is yet to be demonstrated sufficiently, while at the same time, some researchers find futile (Reddy, 2020).

1.4 Research Questions & Objectives

Given the state of resilience theory and assessments described, there are two main research gaps concerning current methods for assessing resilience towards providing actionable tools to guide effective resilience strategies for cities (NAP, 2019):

1. Outside of subjective scorecard-based metrics and qualitative case studies, resilience assessment strategies still rely largely on simplistic methods such as vulnerability and resilience indicator approaches that do not capture the complexity of urban systems subject to disturbances and interactions between the built and natural environment.
2. A second gap involves integrating social and technical domains for resilience assessments, which remains a challenge due to disciplinary and epistemological differences between social and technical domains.

A subset of the second gap is that more nuanced variables in the human dimension such as risk perceptions and community narratives surrounding disasters are difficult to quantify and integrate with measurement or performance-based resilience assessment methods, yet have consequential dynamics with commonly chosen quantitative resilience indicators (e.g., demographics, civic participation, disaster centers) in social, ecological, and technological domains. Another subset, which links the two major gaps, is that hybrid socio-technical network models that simulate resilience to climatic disasters have been called for, but remain largely conceptual and still rely on ad hoc or global structure-based approaches for social metrics toward incorporating the social domain of urban systems (e.g., Bozza et al., 2015; Karakoc et al., 2020).

This dissertation aims to tackle these subset gaps by asking the following overarching research question and related sub-questions that guide the dissertation:

Using Hurricane Maria and Puerto Rico as a case study, how can a multiplicity of resilience assessments be integrated by geographic and network mapping approaches toward better capturing the complexity of urban systems?

The research question above is guided by a series of sub-questions:

1.1. What is the relationship between the resilience of coupled infrastructure systems – essential or critical systems such as energy generation and transmission networks that are coupled with other physical systems like water and communications – and community resilience (e.g., social capital, community bonding, institutional adaptive capacities) for integrated socio-technical systems exposed to climatic disasters like hurricanes?

1.2. How can social vulnerability and impacts to human wellbeing due to climatic disasters like hurricanes be incorporated into a statistical socio-technical model of infrastructure networks toward human-centric recovery efforts?

1.3. What do current disaster resilience indicators capture or ignore in terms of urban social, ecological, and technical complexity, and what are potential pathways toward improving such approaches?

1.4. How can the resilience of complex socio-technical infrastructure systems be understood and assessed from a place-based perspective that includes both subjective experiences and comparative metrics toward resilience-enhancing strategies?

The remaining chapters answer the research questions proposed in this dissertation as follows:

Chapter 2: Developing an Integrated Socio-technical Power Network Failure Simulation to Mitigate Social Hardships. This chapter has been adapted from parts of three manuscripts. The first, “A Simulation Framework for Service Loss of Power Networks under Extreme Weather Events: A Case of Puerto Rico,” by Carvalhaes, T., Inanlouganji, A., Boyle, E., Jevtić, P., Pedrielli, G., and Reddy, T.A., has been published in the peer-reviewed *Proceedings of the IEEE 16th International Conference on Automation Science and Engineering (CASE)*, in 2020. The second, “Social Vulnerability and Power Loss Mitigation: A Case Study of Puerto Rico,” by Boyle, E., Inanlouganji, A., Carvalhaes, T., Jevtic, P., Pedrielli, G., and Reddy, T.A., has been submitted to the International Journal of Disaster Risk Reduction (IJDRR) and is published as a preprint in the *Social Science Research Network* (SSRN Scholarly Paper ID 3838896). The third, “A Human Impacts-driven Framework for Quantifying Disaster-dependent Social Vulnerability: A case study of Hurricane Maria in Puerto Rico,” by Martinez, W., Carvalhaes, T., Jevtic, P., and Reddy, T.A., ready for submission to IJDRR. The chapter answers the first two sub-questions and presents a novel method for developing social metrics for energy infrastructure failure simulations by leveraging treatment-effect approach for Hurricane Maria in Puerto Rico. This chapter contributes to the literature by presenting an index that attributes human hardships to specific disasters events, and a method for weighting predicting factors. The framework demonstrates how a social metric can be framed explicitly in terms of outcomes within the dimensions of human burdens, including psychological, demographic, and economic, to develop a modular simulation toward energy network mitigation toward reducing human suffering.

Chapter 3: Social Vulnerability and Community Resilience Indicators in the Face of Complexity. This chapter is based on the article, “An Overview & Synthesis of Disaster Resilience Indices from a Complexity Perspective,” by Carvalhaes, T., Chester, M., Reddy, T.A., and Allenby, B.R., published in the peer-reviewed journal *IJDRR*, 2021. This chapter answers the third sub-question with a critical literature review and conceptual analysis using a complexity lens. The contribution of this chapter includes outlining the significance of indicators in terms of complexity (or lack thereof), identifying counterexamples that illustrate how a concept or variable is overly simplistic, and alternative framings or methods toward indicators that more pointedly capture resilience principles and dynamics of complex adaptive systems. This chapter aids interdisciplinary research toward metrics that are more clearly differentiated between resilience and vulnerability metrics, and sets the ground for novel indices based on resilience principles and complexity tenets to inform resilience-related policy and decision making in identifying, implementing, and tracking resilience enhancing capacities through a future of uncertainty and continuous hazards.

Chapter 4: Integrating Spatial and Ethnographic Methods for Resilience Research: A Thick Mapping Approach for Hurricane Maria in Puerto Rico. The chapter is based on the manuscript, “Integrating Spatial and Ethnographic Methods for Resilience Research: A Thick Mapping Approach for Hurricane Maria in Puerto Rico,” by Carvalhaes, T., Rinaldi, V., Goh, Z., Azad, S., Uribe, J., Chester, A., & Ghandehari, M., which is currently under review in the peer-reviewed *Annals of American Association of Geographers*, and published as a preprint in the *Social Science Research Network*, 2021 (SSRN Scholarly Paper ID 3863657). This chapter answers the last sub-question and helps link the other chapters toward answering the larger research question in this dissertation. The main contribution of this chapter is a novel framework and methodology for integrating social complexity with performance-based metrics by leveraging distributed ethnographies and a thick mapping approach. Advantages of this approach include built-in flexibility and reflexivity to integrate multiple disciplinary perspectives of a complex adaptive system, which would otherwise be at odds, toward insights emergent from multiple types of resilience assessments, and the identification of weak signals – bits of information about previously unknown dynamics or which indicate low probability but high uncertainty and consequence events. A dynamic and interactive map of Puerto Rico and Maria that can be used as an analytical tool is publicly available.

A final manuscript aids toward a holistic synthesis in the conclusion chapter, “COVID-19 as a Harbinger of Transforming Infrastructure Resilience,” by Carvalhaes, T., Markolf, S., Helmrich, A., Kim, Y., Li, R., Natarajan, M., Bondank, E., Ahmad, N., & Chester, M., published in the *Frontiers in Built Environment*, 2020. The contribution of this article is to identify emerging urban system dynamics and patterns for infrastructure resilience capacities during the pandemic. While the conclusion sections go beyond this article alone, parts of the article have been adapted toward highlighting the complexity associated with resilience in Puerto Rico and the limitations to the systems framings the research in this dissertation is bound by.

CHAPTER 2

DEVELOPING AN INTEGRATED SOCIO-TECHNICAL POWER NETWORK FAILURE SIMULATION TO MITIGATE SOCIAL HARDSHIPS

2.1 The Case for Reduction of Human Hardships in Large-scale Power Network Models

2.1.1 Motivation

Extreme weather hazards, which are geophysical events with the potential to induce extensive physical damage and great social hardships, affect millions of people worldwide (Guha-Sapir, 2020). When vulnerable communities and critical infrastructure are exposed to these hazards, such as the flooding and extreme wind speeds that come with hurricanes, the outcomes are often termed climate-related disasters and cost billions of dollars. For example, the 2005 Hurricane Katrina in the United States cost $125 billion, the 2008 Sichuan Earthquake in China ($85 billion), the 2011 Great East Japan Tsunami ($210 billion), and the 2011 Flood in Thailand ($40 billion). The number of reported climate-related disaster events is increasing worldwide and has tripled in the past three decades (Hillier & Nightingale, 2013). In 2020, over 389 recorded climate-related disaster events resulted in 15,080 deaths and left injured, homeless, or affected 98.4 million people in some way (Guha-Sapir, 2020). Total human loss and monetary costs are commonly reported, but the range of impacts from hazards like hurricanes can span from indirect effects with a slow onset to vicious cycles of vulnerability that hinder sustainable development. For stakeholders and decision-makers in humanitarian agencies, emergency response organizations, and infrastructure management, it is important to have science-driven tools that can isolate the impacts on humans due to disasters so as to guide investments and strategies that reduce social hardship. Social hardship refers to the several types of disaster impacts people must cope with.

Indirect impacts on individuals can be lifelong and chronic. Climate-related losses that cannot be replaced, rebuilt, or valued in monetary terms include the disruption of cultural rituals, communal lifestyles, and the subsequent mental stress and fears of heritage loss (McNamara et al., 2021). Disasters bury or inundate land and damage buildings necessary for cultural practices that support social cohesion, a sense of place and belonging, and spiritual bonds in a community. For children, displacement during critical years of development can result in life-long trauma, inadequate access to healthcare and education and deprive them of long-term security, socialization, and assurance (Dannenberg et al., 2019). The compounding dynamics between socioeconomic status and disasters can lead to increased disparities in income, life chances, gender and ethnic equality, and social status. Over time, the effects of these dynamics can deepen social inequalities or even be transmitted over generations (*GAR*, 2019).

Distress and trauma from disasters can result in short-term and long-term psychological effects. In the short term, disasters have been associated with an increased prevalence of severe psychiatric symptoms, somatic complaints (psycho-physiological symptoms), and nightmares (see Peek and Mileti (2002)). Long-term effects are especially complicated because there may be a latency before onset and intermittent symptoms, but significant post-disaster psychiatric symptoms can remain for as long as 14 years (Bland et al., 1996). Long after a disaster, individuals and communities can endure ongoing mental health impacts, including anxiety, depression, post-traumatic stress (PTSD), and grief that can affect their quality of life (Asugeni et al., 2015; Sattler et al., 2018).

Disasters can aggravate existing social and economic challenges and degrade the sustainability of livelihoods and economic development trajectories for neighborhoods, cities, states, and regions (Adger, 2020; Griffith, 2020; Hillier & Nightingale, 2013; Mochizuki et al., 2014). For example, communities that depend on climate-sensitive resources like fisheries and crops may find their primary way of life devastated and be left without alternatives when faced with extreme environmental disruptions (Adger, 2020; Shahzad et al., 2021). Existing vulnerabilities can result in livelihoods that are subject to a vicious cycle where low socioeconomic opportunities coupled with disasters further drive poverty and environmental degradation, thus making sustainable development goals untenable (see Shahzad et al. (2021)). Families may end up without a home and entire ways of life that provide shelter, sustenance, and economic development (Hillier and Nightingale, 2013). When recovery efforts can no longer be sustained, migration may be the best, if not the only, way to deal with unexpected disruptions (Griffith, 2020), and entire regions may have to rely on external aid to cope with widespread displacement and poverty.

For these reasons, disasters have been a focus of national and international emergency and humanitarian agencies. The United Nations (UN) has identified disasters as an integral part of social and economic development and identified them as essential if development is to be sustainable for the future (*USAID-DRR*, 2019). The UN 2030 Agenda for Sustainable Development reaffirms the urgent need for disaster risk reduction to achieve Sustainable Development Goals (SDG) by reducing exposure and vulnerability of the poor, or building resilient infrastructure that is better prepared and adaptable (Maskrey et al., 2020). Every year, the United States Agency for International Development (USAID) responds to an average of 65 disasters worldwide from hurricanes to violent political conflicts, saving lives, alleviating human suffering, and reducing the socioeconomic impacts (*OFDA*, 2019). The USAID U.S. Foreign Disaster Assistance (OFDA) has highlighted the role of national and local entities, such as local leaders and utilities, in managing disasters and accelerating recovery through sustaining basic services that support life safety and livelihoods.

In the U.S., the Federal Emergency Management Agency (FEMA) has developed an emergency response framework based on Community Lifelines (e.g., electrical energy access) to, *". . . enable all other aspects of society to function."* (*Community Lifelines*, 2020). The Community Lifelines Framework is an example of the role of critical infrastructure like energy systems as networks of assets and capabilities in protecting vulnerable communities during disasters, and supporting the overall resilience and sustainable development of the nation. Even places closer to home in respect to the U.S., such as Puerto Rico (PR), can suffer from insufficiencies in infrastructure management and recovery practices by critical utilities that result in significant human suffering.

In the case of Hurricane Maria in 2017, the centralized power system managed by the Puerto Rico Electric Power Authority (PREPA) took over nine months to recover (Kwasinski et al., 2019). Some estimates account for 3,000 to 4,000 deaths due to Maria, along with massive migrations and displacement (Kishore et al., 2018; Lugo, 2019). At the regional level of the island, electrical infrastructure recovery was driven mainly by storm exposure, remoteness from urban areas, and proximity to power stations, while some of the most vulnerable communities were left behind (Román et al., 2019). Slow electrical recovery extended to interdependent infrastructure, such as communications towers without power, causing sustained anxiety for those wondering about the fate of their loved ones (Lugo, 2019). There was widespread anxiety, depression, crime, civic unrest, public health crises, and a massive migration as the lack of essential lifeline services due to disrupted critical infrastructure systems extended (Lugo, 2019).

As an unincorporated island territory, Puerto Rico is isolated in both geographic and sociopolitical terms. This isolation leads to limited representation, access, and support from mainland institutions with recovery and mitigation capabilities. Such isolated communities are present worldwide and can have limited resources for data acquisition and management, making the providence of decision tools and analysis difficult yet imperative (Beccari, 2016; T. Carvalhaes, Markolf, et al., 2020; Chi et al., 2018). It is of interest to policymakers, infrastructure managers, and other stakeholders that support these communities to have the proper decision tools that help target resilience and mitigation efforts toward reducing human hardships and suffering.

2.1.2 Objectives

Social vulnerability indices are widely accepted and utilized in the literature, are often not the most appropriate metrics to couple with simulations that aim to inform infrastructure preparedness and mitigation toward reducing human hardships. Toward contributing toward the integration of social and technical frameworks for disaster resilience assessments, this chapter addresses the question, *How can social vulnerability and impacts to human wellbeing upon climatic disasters like hurricanes be incorporated into simulations of integrated socio-technical infrastructure networks toward informing human-centric disaster mitigation?*

To improve the robustness of indicators for social impacts for infrastructure network models, a treatment-effect statistical approach will be leveraged to develop a metric that explicitly links response variables based on disaster outcomes that present hardships to communities. The treatment-effect methodology is leveraged for identifying and quantifying factors of social hardships when a population in an isolated community is impacted by specific hazards. This methodology is a template that can be adapted in the context of other isolated or vulnerable regions and infrastructure networks, and can be integrated with technical simulations of engineered infrastructure systems and other impacts (e.g., economic loss and physical and ecological damage) to optimize the allocation of limited resources so as to result in maximum mitigation of human suffering (i.e., social hardships). In turn, the contribution of this framework is to identify the social drivers of human suffering based on objective data (i.e., non-self-reported) while providing a social index that is empirically attributed to a specific hazardous event. Using Hurricane Maria in Puerto Rico as a case study, the specific objectives are to:

1. Estimate the statistical relationships between socioeconomic factors and social hardships in terms of human dimensions of disaster impacts, such as psychological, demographic, and economic effects.
2. Develop a broadly applicable framework based on publicly available data for quantifying social hardship due to disasters at the level of the administrative unit, such as a municipality, using the impact of Hurricane Maria on Puerto Rico as a case study.

After a brief review of power networks, the following sections describe the development of a modular framework for simulating a power network service loss due to climatic stressors, in this case, hurricane winds. The framework is then extended by coupling an established social vulnerability index (SoVI) to demonstrate the implications of accounting for social impacts as a factor for determining the criticality of infrastructure components. Next, an improved approach for social metrics that can substitute for the SoVI is presented. Lastly, a brief argument is made toward the development of social functions as future work.

2.2 Developing a Baseline Socio-technical Model for Power Network Service Loss

2.2.1 Review of Pertinent Literature on Resilience of Power Networks

Power systems can be damaged and disrupted during extreme weather events like hurricanes due to intense winds, flooding, fallen vegetation, and landslides that damage critical components. In the case of Hurricane Maria in Puerto Rico, one of the main factors for power system failures were damaged transmission lines and the poles and towers that support them (Kwasinski et al., 2019). Wind, in particular, is often a primary cause of critical component failures in power networks. For example, Reed et al. (2010) analyzed weather and power outage data after hurricane Rita and concluded that wind speed was the primary determinant of power system damage over heavy flooding.

The disruption and recovery of power networks serve the impetus for power system resilience, which has been characterized by various attributes (e.g., robustness, restructurability), but generally refers to the ability for systems to cope with sudden perturbations and readily return to normal functioning (Bozza et al., 2015; Bruneau et al., 2003; Hosseini et al., 2016; Reddy, 2020. From an engineering systems perspective, power system resilience can be characterized by several temporal stages, often represented by a performance curve (Bruneau et al., 2003; Hosseini et al., 2016; Reddy, 2020)(Figure 2.1). During the disruption phase, the system loses a portion of its function, with the portion remaining speaking to the robustness or vulnerability of the system. The system then follows a delay and recovery phase, followed by a longer-term recovery phase that can include novel adaptations and learning that improves the resilience of the system.

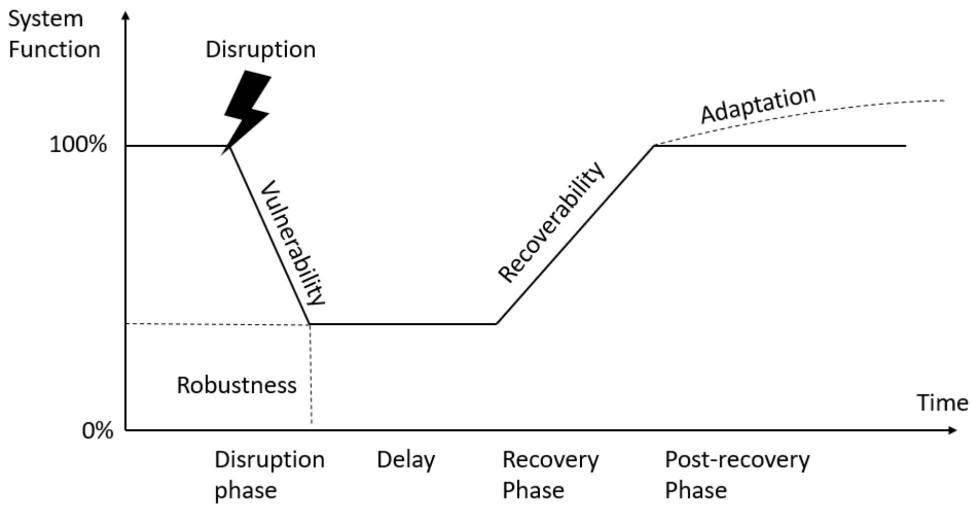

Figure 2.1. Typical resilience curve (also called performance curves) for infrastructure systems disrupted by extreme weather (adapted from Bruneau et al., 2003; Hosseini e al., 2016; Reddy, 2020).

Power network literature has focused greatly on resilience analysis (the ability for systems to respond and recover from disruptions), component vulnerability (the loss or reduction of network performance due to component failures), and modeling mitigation strategies for power systems such as hardening and under-grounding of transmission lines. Generally, relevant approaches can be classified as data-driven methods where non-parametric models for weather hazards and power network responses are leveraged and model-driven where the physical properties of hazards and power systems are leveraged to simulate stochastic processes.

Examples of data-driven approaches include probabilistic windstorm models that train classifiers for the severity of several extreme weather events. For instance, Li et al. (2014) propose such a model using 160 years of historical data to identify six categories of severity according to different wind intensity distributions to analyze network performance and compare mitigation scenarios. Data-driven approaches can also include risk assessment frameworks that leverage Monte Carlo simulations to generate storm conditions (e.g., extreme wind, lightning) that distributed power networks are subject to (e.g., Rocchetta et al., 2015).

Model-driven approaches largely focus on spatio-temporal stochastic models and fragility curves for network components toward capturing the propagation of hurricanes across space and time. Using linear fragility curves, for example, Muhs and Parvana (2019) leverage historical data to generate spatio-temporal hurricane scenarios and map power network failures. In the specific case of extreme winds, Pantelli et al. (2017) develop fragility models for individuals components and the power network as a whole to conduct experiments on a reduced version of the Great Britain transmission network. Such studies often aim to determine the criticality of network links and nodes as a function of wind speed to inform and model targeted mitigation strategies toward reduced network vulnerability (e.g., Ouyang & Dueñas-Osorio, 2014).

A power network comprises several interconnected classes of components, including generators, substations, transmission, and distribution lines. Given the networked nature of energy infrastructure, it is vital to incorporate the interconnected structure of the system to capture the dynamics of power flows from generation to distribution (i.e., endpoints) (Pobočíková et al., 2017). Topological models thus help capture the geographic heterogeneity of disaster impacts, changes in the topology of power networks, and changes in simulated disturbances like hurricanes (Boyle et al., 2021). Whereas such models generate topological metrics that analyze network performance, component-based topological models further incorporate the physical processes of power flows for more accurate simulations (e.g., generation capacity, voltage capacity, demand at end nodes).

Currently, established approaches for models of large scale power systems that integrate infrastructure and social considerations (e.g., social impacts or vulnerability to disasters) leverage composite social vulnerability indices as a method for social metrics that indicate human burdens, impacts, and abilities to recover from infrastructure service losses due to disasters. Such methods aim to address the fact that traditional methods for network models tend to take only financial costs or social burden as a monetized measure or total population affected, and therefore ignore other dimensions of human hardships, such as the impacts that manifest in the experiences of communities along psychological, demographic, and sociopolitical dimensions.

Composite indices are attractive because they largely rely on data that is already publicly available, along with relatively simple calculations (e.g., a simple additive composite of normalized or standardized variables), if not already publicly available as a precalculated metric. One popular method is the Social Vulnerability Index (SoVI) which leverages Census data to map relative vulnerability based on state, county, or Census tracts (Cutter et al., 2003; Flanagan et al., 2011). The SoVI is of the most practical and traditional approaches because it readily relates to components of technical models due to its spatial nature, is based on publicly available data, and can easily be adapted for particular contexts and relevant data (Bozza et al., 2015; Fernandez et al., 2016; Holand & Lujala, 2013). Lo Prete et al. (2012) have leveraged the SoVI directly in a microgrid simulation to assess the reliability and sustainability of regional grids. Recently, Karakoc et al. (2020) used a reduced version of the SoVI to integrate social vulnerability into an interdependent infrastructure network simulation subject to disruptions. These approaches show the additional advantages due to the spatial nature of these widely accepted indices, making them amenable to connecting to network components, such as transmission and distribution lines.

2.2.2 Overview of Modular Component-based Methodology for Power Network Failure Simulation

Carvalhaes et al. (2020) introduced a probabilistic approach for Component-based Event Simulation (CBES) that generates sets of stochastic hurricane events and component failures to simulate service levels per municipality in PR. The approach is composed of key modules (wind speed generator, network breakage generator, and power flow model) outlined in Figure 2.2.

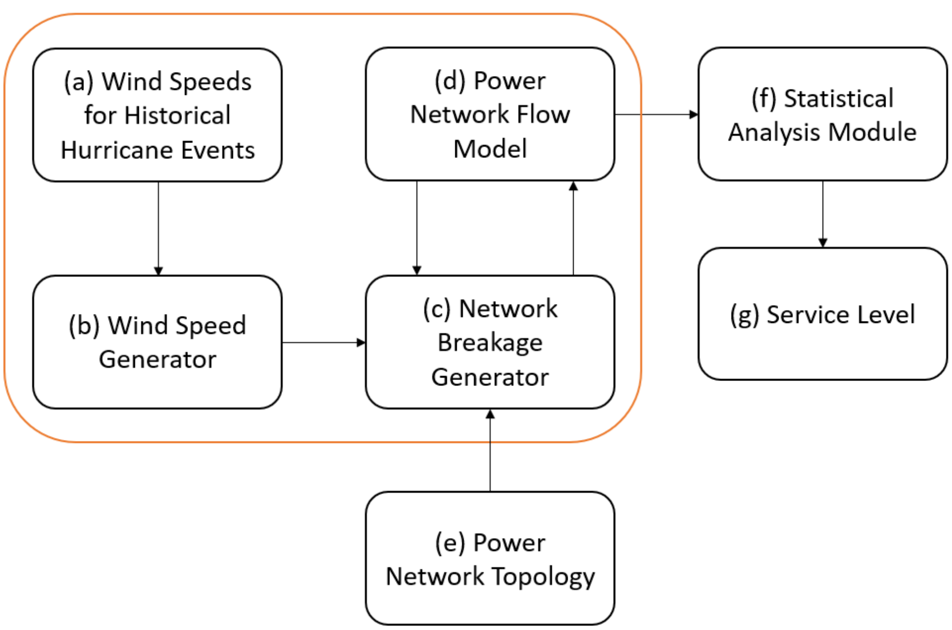

Figure 2.2. Main components (i.e., modules) of the CBES simulation framework.

Historical hurricane data for maximum wind speeds (a) are used to generate weather event scenarios (i.e., maximum hurricane wind speeds) in module (b). See section 2.2.4 for details on hurricane wind data estimations for Puerto Rico. Generated stochastic maximum wind speeds correspond to failure probabilities for each transmission line segment in the network topology (e) to generate realizations of breakages for each transmission line via the Network Failure Generator (c). The power network model (d) leverages the topology, generated breakage data, and power flow properties to balance the supply and demand of power. Lastly, the statistical analysis module (f) generates numerical experiments to analyze the effects of weather hazards, in this case, extreme wind due to hurricanes, to output estimated average service levels (g) for each municipality. In this way, the CBES framework enables the analysis of component failures on the performance of the network, and the modeling improvements to specific components to inform infrastructure policy, design, and management toward making the most of constrained resources (e.g., alternative topological designs and line hardening strategies).

2.2.3 Application to PR: Defining a Topology for the PREPA Centralized Power Transmission Network

Since transmission lines were the leading cause of network failure for the centralized Puerto Rico Electrical Power Authority (PREPA) system due to Hurricane Maria, these components were of focus for the topological model. While geospatial data for the Puerto Rico power network are publicly available[1], they were derived primarily via remote sensing techniques and appeared not to be up to date or topologically validated in respect to the conditions during Maria. To develop a valid and workable topology, two reports were used to determine the PREPA network topology in Puerto Rico: The Fortieth Annual Report (*PREPA*, 2013) and the Puerto Rico Integrated Resource Plan (IRP) 2018-2019 (2019). Both reports provide maps that illustrate the locations and interconnections of power system components. The Fortieth Annual Report shows the planned transmission system for 2018 and thus includes legacy components along with planned installations (Fig. 2.3). The 2019 IRP report shows the current generation map as of the writing of the report (2019), which includes transformers and transmission lines (Fig. 2.4).

Both maps are limited, so assumptions are required. The exact geographic location of generation stations and the respective connections to the transmission system in the Consultant Report is not always clear. The IRP map does not include a legend, and the transmission lines appear to be simplified. Additionally, parts of the IRP map are covered by large labels, which may obscure system components and connections. While

[1] Available: https://hifld-geoplatform.opendata.arcgis.com/datasets/electric-power-transmission-lines/data?geometry=-68.682,17.734,-63.45,18.647

the IRP map was given preference based on the data being more recently published, the Consultant Report map is more precise and detailed. Therefore, both maps were considered to cross-reference information. Nonetheless, some assumptions still had to be made.

Images of each map were georeferenced in a GIS to determine their approximate coordinates and develop a topology for modeling system behavior and outcomes due to perturbations and failures. Where connections between generators and transmission units were unclear, the nearest unit to the respective generator was assumed to be connected. This assumption was especially necessary for the San Juan plant in the Northeast, which is surrounded by a greater density of components. Pseudo nodes (line vertices that cross without a connecting power unit) and proposed underground lines were not included in the topology. Switchyards were also not considered due to the modeling scope and since they are not present in the IRP map.

The resulting topology includes eight generators, 13 230kV transformers, and 47 115kV transformers (Fig. 2.5). Transmission lines represent simplified versions of the IRP map and thus are a “semi-geographic” version of the topology. Therefore, where connections between generators and transmission units were unclear, the nearest units were assumed to be connected. Pseudo nodes (line vertices that cross without a connecting power unit), switchyards, and underground lines were not included in the topology. Lastly, end points for power service were generalized as aggregate nodes based on municipality centroids that connect to the nearest 38kv substation. The links between these end points and substations can be assumed as an abstract of the distribution level of the network, which is otherwise outside of the scale of the CBES simulations in this chapter.

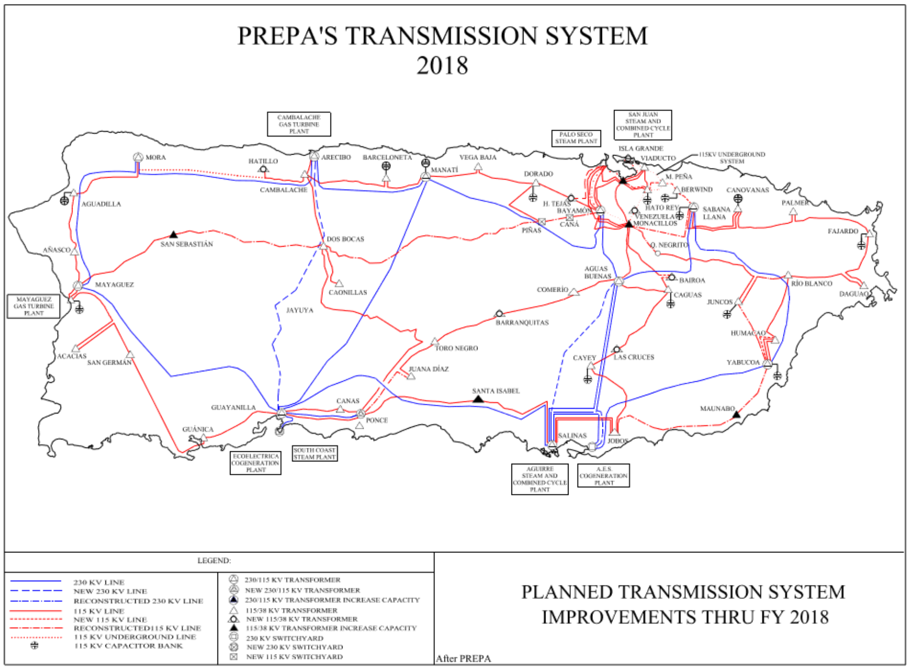

Figure 2.3. PREPA planned transmission system for 2018 from Fortieth Annual Report (2013) Source: https://aeepr.com/en-us/qui%C3%A9nes-somos/portal-inversionistas/financial-information.

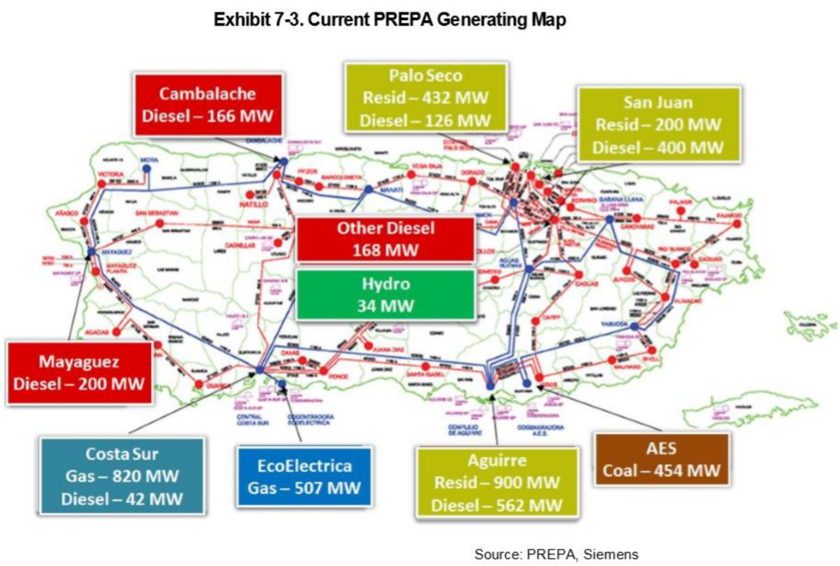

Figure 2.4 Current generating map from IRP 2018-2019 report (Source: aeepr.com).

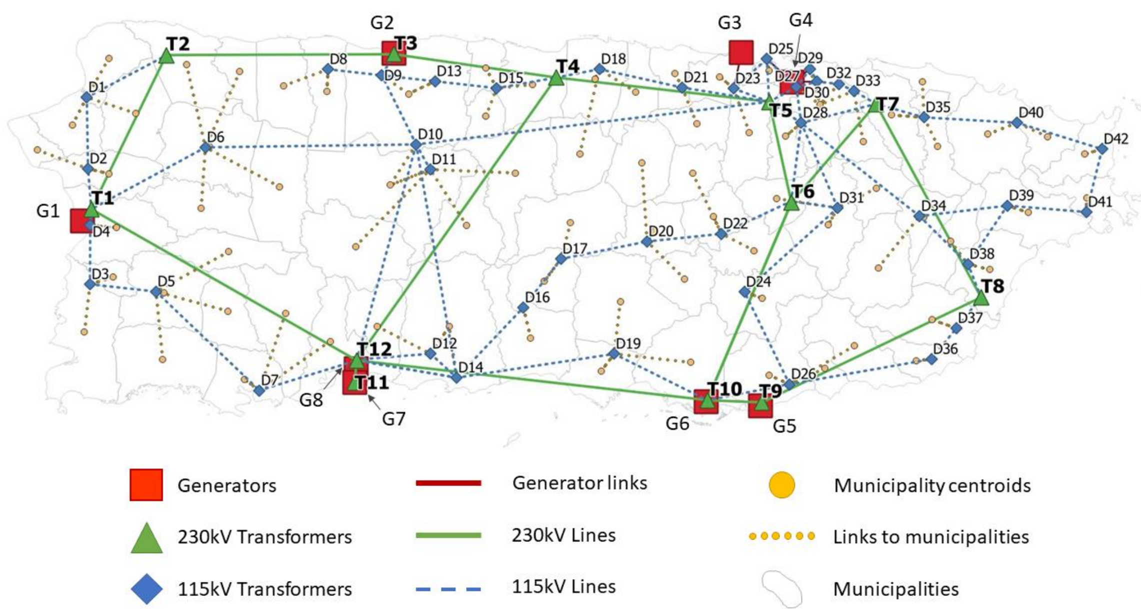

Figure 2.5. Geographic representation of the modeled topology. Generators are indexed with the prefix "G" and sequential numbers clockwise starting from Mayaguez (e.g., G1). Transformers at the 230kV level are indexed with the prefix "T" and sequential numbers clockwise starting from Mayaguez (e.g., T1). Transformers at the 115kV level are indexed with the prefix "D" and sequential numbers from West to East (e.g., D1).

2.2.4 Estimating Hurricane Wind Speeds with Limited Data

The availability of applicable climatological metrics and statistics is one of the main barriers for simulations of power network reliability under environmental stressors (e.g., Cadini et al., 2017). In terms of wind data, such metrics are usually captured by radar systems (e.g., NOAA NEXRAD) or measured locally by instrumentation at specific weather stations. While radar is available for several events in many parts of the United States, it becomes challenging when many events over several decades are needed because data types and instrumentation change as radar programs evolve over time. This limitation is especially challenging in Puerto Rico, where there are few radar stations, which sometimes break during intense storms such as Maria (Samenow, 2017).

To overcome this hurdle and obtain a reasonable number of storm events, data from NOAA's Global Summary of the Day (GSOD) based weather stations in Puerto Rico were leveraged. Maximum sustained wind speed (knots) for all available weather stations in Puerto Rico between 1943 and 2020 were queried so that 45 tropical storm events could be subset using respective date ranges. As weather stations are installed or go out of commission over time, the total number of observing stations can vary. Thus, D=28 of the 45 subsets were selected based on a total number of ≥4 stations, a relatively even distribution of the stations across the island (e.g., avoiding four stations all located between the Western and Northern coasts), and the availability of hurricane track data to supplement the weather station values. Each subset date range for each event was then queried for maximum sustained wind speed (MSWS), resulting in georeferenced data points for 28 tropical storm events (i.e., shapefiles). In an automated batch process, the shapefiles were split by event and interpolated into 1km grids (i.e., GeoTIFF rasters) via inverse distance weighted interpolation (IDW) with a standard squared weighting coefficient for the spatial extent of the main island of Puerto Rico. This method was chosen based on the relatively low number of observed data points so that all points can be used as samples and so that the influence of a given observed point on nearby unknown points is limited. Lastly, the maximum MSWS value within each municipal boundary was extracted using a Census TIGER/Line shapefile and exported as a table with maximum MSWS values for 28 events per municipality. There are 78 municipalities in Puerto Rico, which are analogous to counties in Census databases. Two municipalities are the small islands of Culebra and Vieques located off the main island's East coast, which are not connected to the centralized electrical power network, so they are not included in this study or respective data processing.

The resulting MSWS values tended to be significantly lower than expected or those reported by other data sources, especially for events making landfall in Puerto Rico. These low estimates are potentially due to local effects regarding topography, land use, or because MSWS metrics are obtained through the daily mean of hourly observations. Therefore, MSWS values were scaled to the maximum wind intensity (knots) of the closest data point along the storm track[2]. The National Hurricane Center's (NHC) International Best Track Archive for Climate Stewardship (IBTrACS) for each of the 28 events was leveraged to scale maximum MSWS values for each weather station to the

[2] Storm track data was not used as the primary source of data because it offers only vector points along the path of the hurricane, which does not capture the spatial distribution of wind speeds along the entire surface of Puerto Rico.

nearest data point along the IBTrACS path[3], and subsequently, the distribution of MSWS values for each municipality. The last step is linking the MSWS data to transmission lines to simulate component failures.

The maximum wind speed values (MSWS) were linked to transmission based on which municipalities a transmission line edge intersects (assuming that the maximum wind speed is uniform within each municipality) using a GIS workflow where transmission line and municipality boundary data were transformed into polylines and intersected[4]. The table from the resulting shapefile is a list of municipalities that each link crosses, which is then used to reference the MSWS values that stress transmission line edges.

2.2.5 Coupling a Social Vulnerability Index (SoVI) with a Stochastic Power Network Failure Model

Leveraging the CBES framework from Carvalhaes et a. (2020), a social vulnerability dimension to the network model by leveraging SoVI (Boyle et al., 2021). The SoVI previously described could readily provide a metric that helps power network simulations go beyond fiscal-based social variables (e.g., Vugrin et al., 2014) and automate the process of index-based decision-making. In this way, the complexity of infrastructure network failures from a socio-technical perspective can be analyzed and

[3] This was batch processed using the "Distance to Nearest Hub Tool" in Quantum GIS.

[4] Using the "Line Intersect" tool in QGIS to create a point layer that assigns an XY point for each intersection between municipality boundaries and transmission lines.

simplified, allowing stakeholders to take more comprehensive and socially aware considerations toward investing in resilience-enhancing strategies for energy infrastructure.

A socio-technical indicator was developed as an integrated impact metric for each power network component (i.e., transmission line segment in the power network topology). At the municipal level, the indicator is a function of service level loss and the SoVI so that each Megawatt-hour of service loss is weighted by its relative impact on the system on social vulnerability by way of the SoVI. The social vulnerability-weighted service level loss, sv_i, is calculated simply for each municipality as,

$$sv_i^{(1)} = (s_i - s_i^*)\, v_i$$

where s_i *and* s_i^* are the power supply service levels before and after the hurricane event, respectively, and v_i is the SoVI as a weight that is scaled such that $\sum_{i=1}^{n_m} v_i = 1$. Alternatively, following the exponential approach by Karakoc et al. (2020), the sv_i can be calculated as:

$$sv_i^{(2)} = (s_i - s_i^*)\, e^{av_i}$$

The latter method enables the relative weighting between service loss alone versus social vulnerability impacts. In other words, when $a = 0$, only the level of service loss is considered, while the greater the value of a, the greater priority is given to social vulnerability. While a downside of this method is that there may be no straightforward or objective way to determine the value of a, this choice can be leveraged by stakeholders and decision-makers as they best see fit.

Figure 2.6 shows results considering service loss only, and Figure 2.7 shows results according to $sv_i^{(1)}$ and $sv_i^{(2)}$ averaged across 10, 000 simulations, where $a = 10$ for the latter to illustrate the effect of considering SoVI as a weight for service loss. These results demonstrate how high levels of service loss alone do not always correspond to high levels of social vulnerability. That is, although two adjacent municipalities may suffer similar impacts to service losses, the impacts of these losses on social vulnerability may differ significantly.

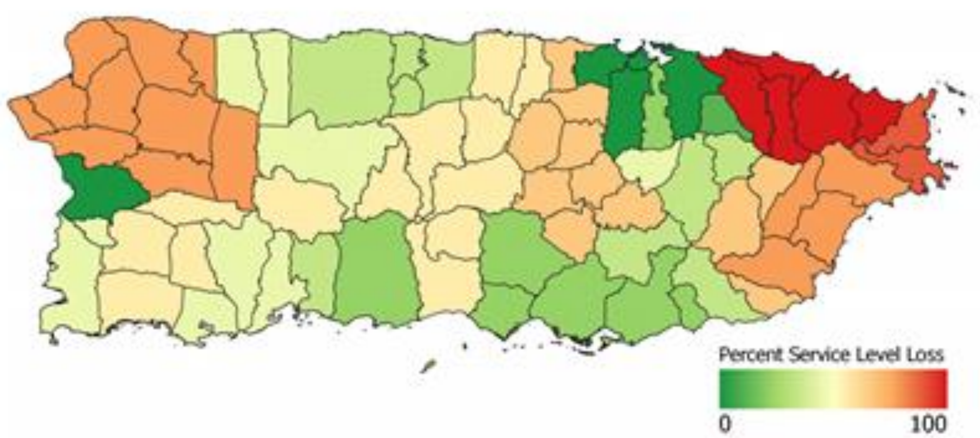

Figure 2.6. Percentage of service level loss in each municipality averaged across 10,000 simulations in CBES.

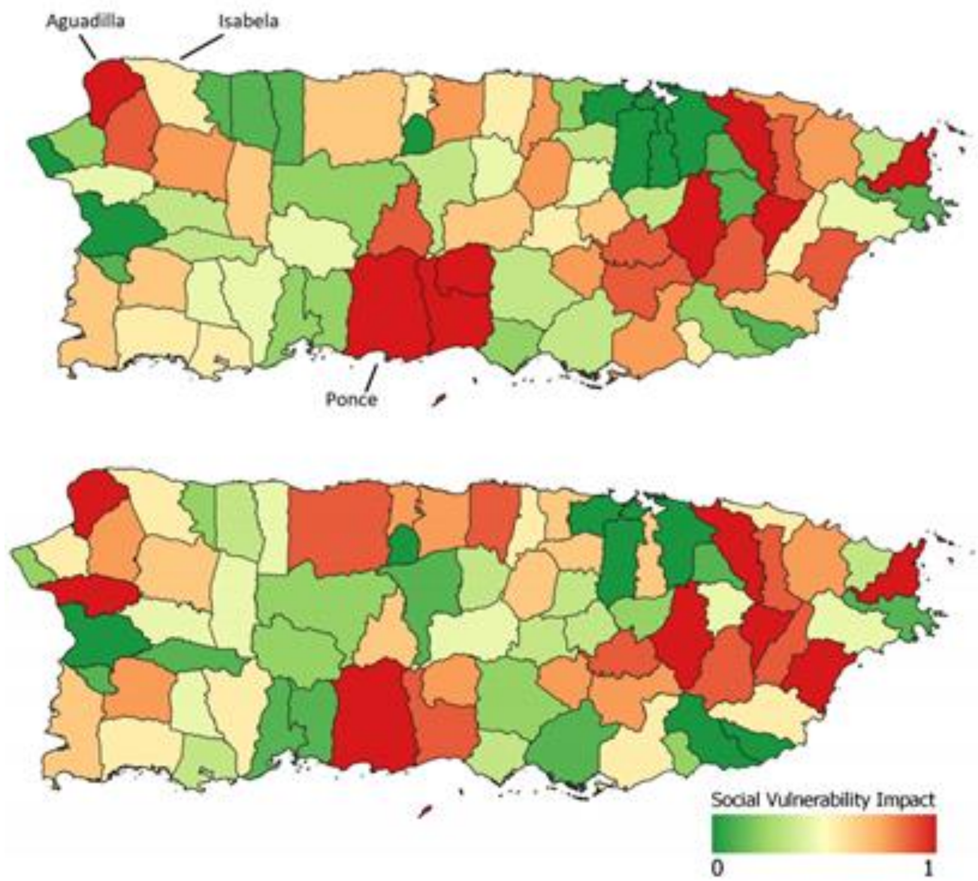

Figure 2.7. Social Vulnerability Impact modeled according to $sv_i^{(1)}$ (top) and $sv_i^{(2)}$, assuming $a = 10$ (bottom) for each municipality averaged across 10,000 simulations.

This model can be further leveraged to test line hardening schemes, such as undergrounding cables, toward mitigation policies aimed at reducing social vulnerability. As an illustration, two transmission lines were selected based on their relative impact on total service loss. Namely, the fragility distributions for Line A and Line B in Figure 2.8 were shifted such that these lines essentially do not break under the modeling assumptions and hurricane scenarios of this study. Figure 2.9 shows results for an additional 10,000 simulations assuming each scenario of hardening one of these two lines. While the spatial patterns are not starkly different across the island between each line hardening scenario, hardening Line A produces altogether lower vulnerability impacts as a fraction of total vulnerability-weighted total power loss.

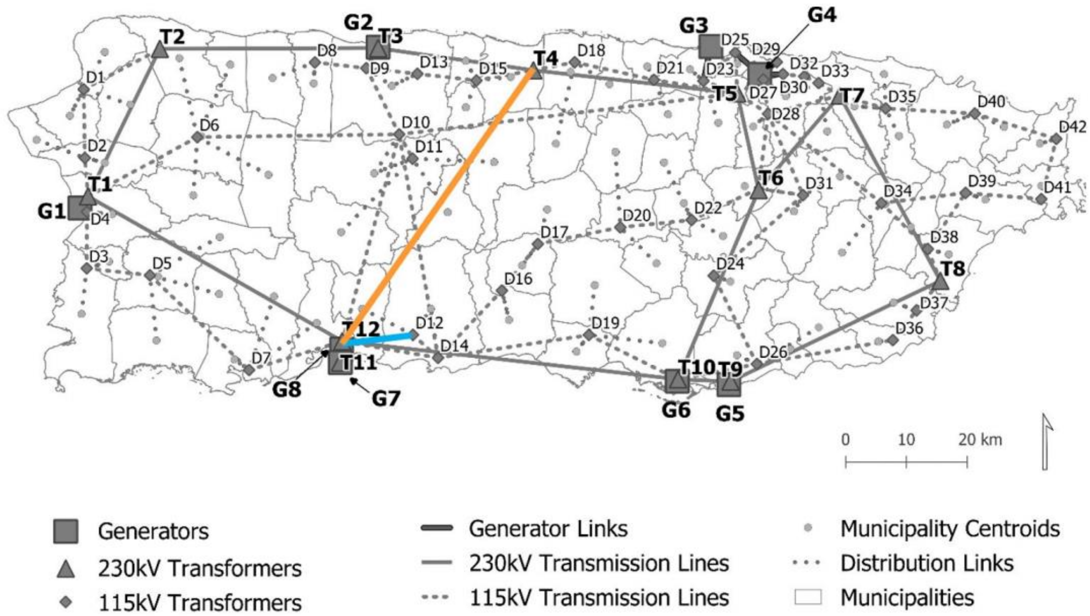

Figure 2.8. Transmission line hardening scenarios are represented by Line A in blue and Line B in orange.

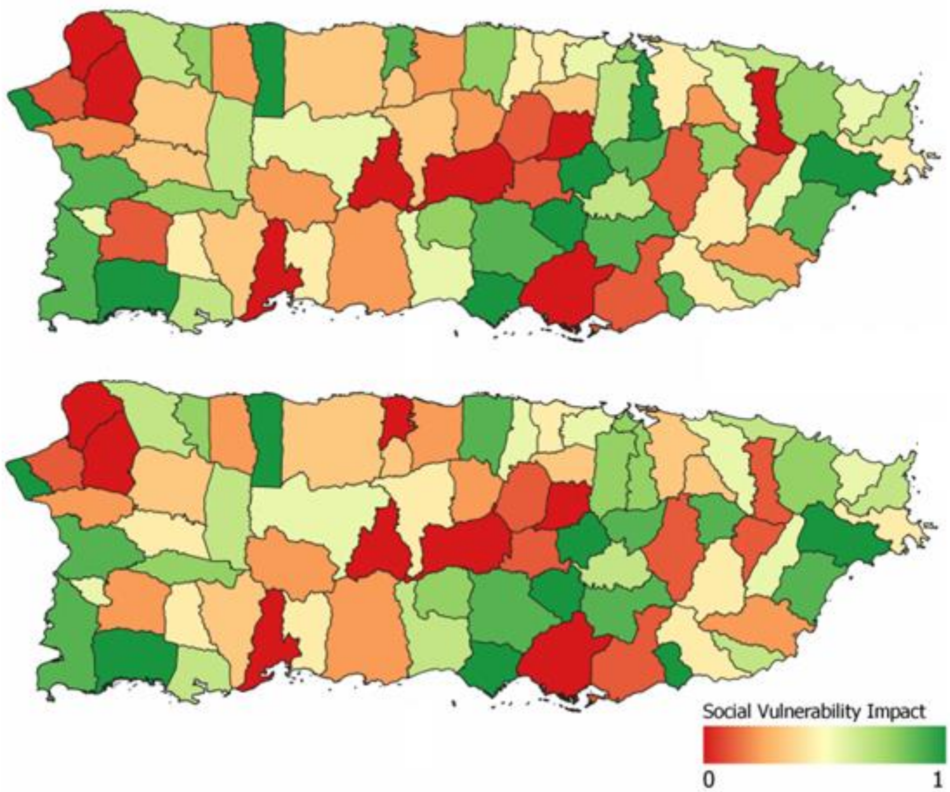

Figure 2.9. Social vulnerability after hardening Line A (top) results in an average overall vulnerability impact of 40.5%. Social Vulnerability after hardening Line B (bottom) results in an average overall vulnerability impact of 43.5%.

The CBES and coupled SoVI-CBES frameworks described in this section represent a modular pipeline for identifying critical network components (i.e., transmission lines) toward reducing social vulnerability and human suffering. The next section describes an alternative framing oriented around social hardship as realized vulnerability and a more advanced method for developing a metric that can be substituted for the SoVI toward reducing social hardships.

2.3 A Treatment-Effect Social Social Hardship Index (TESHI) Framework

2.3.1 Limitations of Static Social Vulnerability Indices

When exposed to an environmental hazard, individuals and communities do not all have the same opportunity to properly anticipate hazards, sufficiently prepare, and recover after an event. Social hardships emerge from the present historical, cultural, and socioeconomic circumstances of a hazard-affected location (Cutter et al., 2003; Wisner et al., 2004). However, quantifying disaster-related social hardships and the associated drivers behind them is challenging due to the complex nature of social vulnerability and the challenges of measuring human suffering.

In the disaster risk domain, (Cutter et al., 2003) introduced a composite index method based on Census data that rank orders U.S. counties using indicators of structural qualities of social vulnerability (e.g., household composition and language as proxies for sensitivity to disruptions, ability to evacuate, and access to resources). Indices are usually composed of various indicators that are combined into a single aggregated metric. Several formulas exist for aggregation methods, including a straightforward summation of normalized values, averaging, or factor analysis, and can be weighted and non-weighted (Beccari et al., 2016). Such indices have been attractive for both researchers and practitioners because they reduce the complexity of multidimensional issues (like social vulnerability and resilience) into relatively communicable, straightforward, and adaptable metrics (e.g., vulnerability maps)(OECD, 2008; Vincent, 2004). For example, a composite index framework was adapted and ultimately used to develop the U.S. Centers for Disease Control (CDC) Social Vulnerability Index (SoVI), which is a publicly available map-based online tool (Flanagan et al., 2011). More comprehensive indicator frameworks have since emerged, such as the Baseline Resilience Index for Communities, which incorporates dimensions of social resilience or the ability to recover and adapt (Cutter et al., 2010).

Important shortcomings have been identified in the methodology used to determine these indices, however. The most common approaches are composite indices that are constructed ad hoc and lack formal validation of variables and models (Beccari et al., 2016). There is an ongoing challenge for indices to be validated with dependent variables that proxy realizations of vulnerability (Fekete, 2019). For example, the number of people suffering flood damage after an event, the number of people seeking shelter, or individuals' satisfaction with damage compensation can be deemed responses for validation of proposed vulnerability indicators. Carvalhaes et al. (2021) have further identified the sustained insufficiencies in grounding social metrics with clear disaster outcomes (external validity) and improved quantitative methods toward selecting and weighting key variables. Fekete (2019) has outlined external validity challenges in terms of capturing "revealed vulnerability" to define validation criteria, including varying interpretations of vulnerability and uncertainty in attributing validation criteria to a recent disaster since demographics and societal dynamics may have evolved. Furthermore, there is still a need for disaster-level benchmarks that capture revealed vulnerability toward a global database of disaster cases.

Both qualitative and quantitative techniques have been explored to address these shortcomings (*FEMA*, 2021). Some studies rely on interviewing experts in the field, such as emergency responders, local leaders, and infrastructure managers, to validate indicators using tacit although subjective knowledge (e.g., (Tate, 2013). In such cases, researchers and practitioners may provide a visual inspection of a map, or experts may filter, rank, or weigh a selection of indicators that make up an aggregate measure. Quantitative approaches have leveraged the SoVI and related frameworks alongside statistical techniques to tie sociological drivers (e.g., income, age, household composition) to disaster outcomes. For example, Yoon et al., 2016) leveraged well-established indicators for composite indices using factor analysis, Ordinary Least Squares Regression (OLS), and Geographically Weighted Regression to develop a Community Disaster Resilience Index (CDRI). The method relied on total human loss and property damage as response variables for a linear model. The response variables are relevant to social hardships but do not adequately capture the multiple dimensions of human-centered disaster impacts, such as loss of livelihoods and psychological distress.

Non-monetary social impacts (i.e., outside of economic valuation) remain underacknowledged, and research with loss and damage associated with slow-onset effects (e.g., post-traumatic stress, cultural heritage loss) is nascent (McNamara et al., 2021). A research gap remains regarding the statistical investigation of the relationships between disasters and societal impacts. Research has been overly focused on GDP and institutional capacities (e.g., foreign aid) while overlooking the suffering that people experience during and after disasters (Mochizuki et al., 2014). A remaining challenge is to design and validate a non-economic social metric using publicly available data to guide mitigation efforts and infrastructure robustness in the face of future disasters.

2.3.2 Framing Human Dimensions of Social Hardship and Related Data

The potential for human hardship given socioeconomic and demographic structures that determine the sensitivity of a household or community at risk can be thought of as social vulnerability to environmental hazards (Cutter et al., 2003; Engle, 2011). Vulnerability is then the likely predisposition of a community to hardships due to climate-related or human-induced disasters, while community resilience can be interpreted as the capacity for a community to recover and adapt during the disruption of critical urban functions (Aldrich, 2012). However, social vulnerability and resilience metrics represent baseline conditions or are based on societal predispositions to potential risks rather than definitive human-centered impacts of disastrous events.

The problem is that one needs a distinct measure of the hardship experienced by a community, either in the form of a direct measure or a surrogate. However, current approaches are either qualitative, do not have a clear association with the hardship due to a calamity, or use consolidated groups of metrics with only a tangential association to manifestations of social hardship. For example, the conflation of social vulnerability, resilience, and burden can compromise the intended uses of social metrics for planning and modeling frameworks (Carvalhaes et al., 2021). While quantitative indicators have been established for social vulnerability and community resilience, there are two major shortfalls: (1) There is a need for social indices that are validated with a response variable (Beccari, 2016; Yoon et al., 2016), (2) social vulnerability and resilience indicators do not account for the manifested hardships that are a direct result of a disastrous event (Béné et al., 2014; Eakin et al., 2016).

To focus on the direct human hardships endured by communities due to Maria, an alternate framework is proposed based on the dimensions of social impacts of disasters as summarized by the National Academies (*NAS*, 2006). In this synthesis report on social science contributions to disaster risk, outcomes of human suffering and loss are outlined in terms of four key dimensions: psychological, demographic, economic, political. Representing the major axes along which human beings experience hardships induced by disasters, these are leveraged dimensions to frame our model specification and interpretation. Table 2.1 presents common disaster impacts along each of the four human dimensions as an example of our conceptual framing of social hardship. Using Hurricane Maria in Puerto Rico as an example of a larger approach, a modeling framework is proposed toward quantifying social hardship due to disasters that is grounded in objective responses to a hazardous event that clearly relates to human dimensions of disaster impacts.

Table 2.1: Human dimensions of disaster impacts with examples of common impacts as working response variables (see NAS, 2006).

Dimensions of Human Impacts	**Common Post-disaster Outcomes**
Psychological	Increases in suicide and substance abuse rates
Demographic	Excess mortality, migration
Economic	Public aid requests, higher unemployment
Political	School closures, civil unrest

2.3.3 A Treatment-Effect Approach for Estimating Realized Social Vulnerability

Treatment-effect speaks to the effect of a binary variable (0-1) on an outcome of interest (Angrist, 2016). The binary variable is thought of as a “yes” or “no” in terms of whether a given subject has been exposed to a specific treatment. The treatment-effect framework originated in medicine to determine the effects of treatments such as experimental drugs and new surgical procedures (). In such cases, there is a group of patients that receive the new treatment (i.e., the experimental group, or “1”) and a group that does not (i.e., the control group, or “0”). Treatment-effect methodologies, which can range from regression-based techniques to instrumental and social experiments, are now widely used in econometrics to determine the effect of government policies, social programs, subsidies, and personal choices like college attendance (Heckman & Vytlacil, 2007).

Toward the development of social metrics for disasters, a treatment-effect framework can be used by leveraging panel data (a time series of observations before and after an event) to measure the effect of Hurricane Maria on social outcomes. In this case, the treatment is Hurricane Maria as an environmental intervention that changes the living conditions of exposed communities (i.e., the people of Puerto Rico), which in turn, manifests as outcomes of social hardship. Such outcomes include those along human dimensions of disaster impacts outlined in Table 2.1, which can be captured by observational data to proxy the socioeconomic and living conditions before and after Maria. However, the problem is that the occurrence of Maria and its exposure to Puerto Rico’s population precludes the ability for outcomes to be observed had the event not occurred. That is, we cannot observe the counterfactual condition, which is a well-known limitation for such cases (Dehejia & Wahba, 1999).

Martinez et al. (2021) addressed this issue specifically for the context here outlined (i.e., constructing a treatment-effect model for Hurricane Maria in Puerto Rico) by leveraged the proposed social hardship framework (Table 2.1) and panel data techniques to estimate the counterfactual condition (i.e., backcasting trends in variables including mortality, suicides, median house prices, and employment for 2016-2017. Table 2.2 outlines the response and predictors used by Martinez et al. (2021) within the social hardship framework described in section 2.3.2.

Table 2.2. Treatment affect model specifications using the social hardship framework from Table 2.1. Predictor sets listed in the third column are detailed in the following Table 2.3.

Human Dimension	**Response**	**Set of Predictors (Table 2.3)**	**Data Source**
Psychological	Suicides (S) Substance Abuse (SA)	I – VI I – VI	Substance Abuse and Mental Health Data Archive (SAMHDA).
Demographic	Excess Mortality (EM)	I, IV – VIII	Milken Institute School of Public Health
Economic	Median Home Price (MHP) Employment Rate (ER)	I, III – VII I, III – VII	U.S. Census

Table 2.3. Predictors for treatment-effect model that correspond to Table 2.2.

Predictor Set	Description	Time Series
I	Age groups: 5 – 17, 18 – 34, 35 – 64, and 65 – 74 years	2012 – 2018
II	Cognitive Disability (% population per municipality with any cognitive disability)	2012 – 2018
III	Health Insurance (% population per municipality with health insurance coverage)	2012 – 2018
IV	Unemployment rate	2010 – 2018
V	Gender	2010 – 2018
VI	Income per capita	2010 – 2018
VII	Ratio of large vs. small businesses	2012 – 2018
VIII	Stratus (% population in lowest, mid, highest socioeconomic development level. See Santos-Burgoa et al., 2018)	NA

Martinez et al. (2021) further use the results of this model to develop an index for each response using a linear combination of the set of significant predictors. Results of these indices based on the treatment effect model include versions for the intervention and counterfactual, and are summarized in Figure 2.10. By comparing the counterfactual estimates (the forecasted trends, had Maria not occurred) with observed responses after Maria as the treatment, it is possible to model the effect of Maria on social hardship.

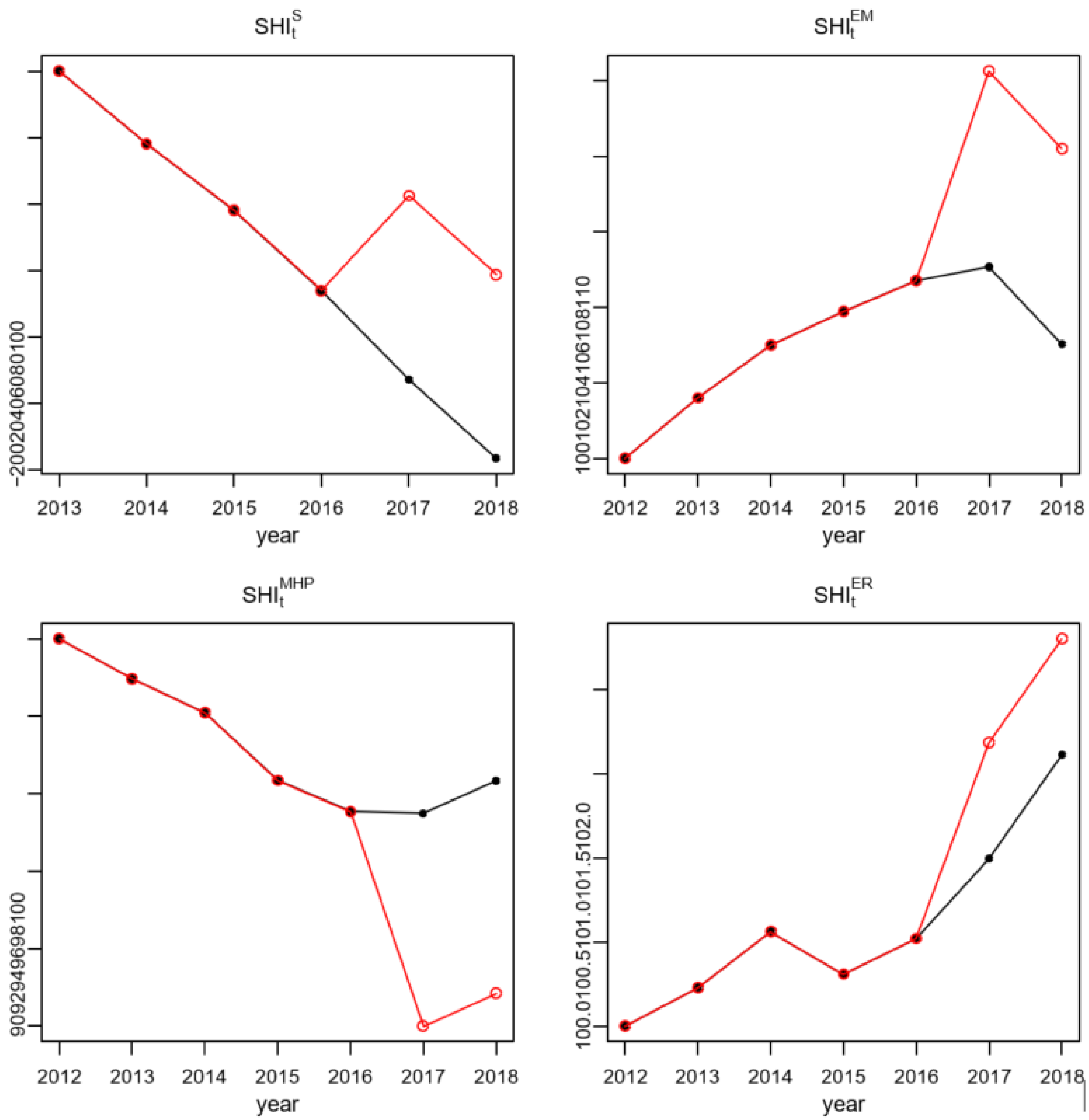

Figure 2.10. Sub- Index (SHI) results for each social hardship response: suicides (SHI_t^S), excess mortality (SHI_t^{EM}), median home prices (SHI_t^{MHP}), and employment rate (SHI_t^{ER}). The red lines show the indices with the Hurricane Maria effect (intervention) and the black lines without considering the Hurricane Maria effect (forecasted counterfactual).

2.3.4 Developing a Composite Social Hardship Index with Treatment-Effect Estimates

To develop a composite Treatment-Effect based Social Hardship Index (TESHI), it is here proposed to first construct a sub-index (SHI) for each response used in Martinez et al. (2021) by taking the difference between the indices for the intervention and counterfactual conditions (i.e., the "jumps"; or vertical spaces between the red and black lines in Fig. 2.10). These differences thus represent the marginal effect of Maria on each response variable. Because these marginal effects have a significantly different range of values for each response, a min-max scaling method is first applied to each sub-index so that values range from 0 – 1: equation.

Lastly, a composite is proposed as a summative aggregate of the sub-indices that correspond to each response (i.e., social hardship outcome), such that:

$$TESHI_t\,(\omega_1,\omega_2,\omega_3,\omega_4) = \omega_1 SHI^S{}_t + \omega_2 SHI^{EM}{}_t + \omega_3 SHI^{MHP}{}_t + \omega_4 SHI^{ER}{}_t$$

Where $TESHI_t$ is the composite index for a given intervention (hurricane or disastrous event) that occurs at time step, t, and the weights ω_m with m = 1, ..., 4 are determined ad-hoc according to the relevance of each response.

To illustrate the approach, a *TESHI* was calculated for Hurricane Maria, assuming the marginal effects of the intervention for the year 2017. Since response variables can have either a positive or negative relationship with vulnerability, the sub-indices SHI^{MHP} and SHI^{ER} were multiplied by *-1* since an increase in these sub-indices are considered an indication of lesser hardship (Cutter et al., 2010; Flanagan et al., 2011).

2.3.5 Results of Applying TESHI Methodology to Hurricane Maria in Puerto Rico

Figure 2.11 shows the composite $TESHI_{2017}^{PR}$ assuming a series of differing assumptions for weighting schemes to show how the index varies based on stakeholder preferences rather than equal weighting. Visual inspection of the maps shows that the spatial distributions and clustering of hardship can differ depending on how responses are weighted. Additionally, decomposing the index by response shows that index values may cluster differently in space between responses. Such dynamics that emerge between the composite and sub-indices can be helpful for the interpretation and future development of TESHI-based planning tools geared toward stakeholder needs.

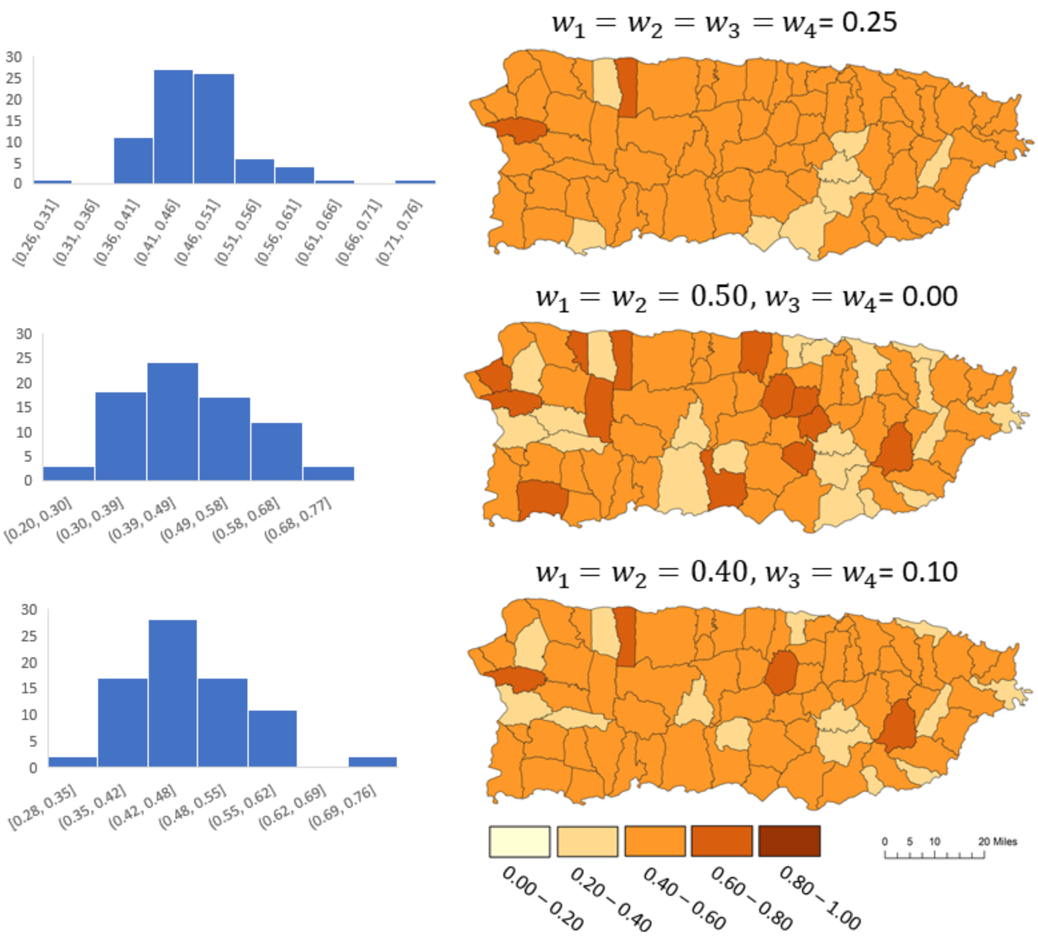

Figure 2.11. Composite Social Hardship Index for Hurricane Maria in Puerto Rico, 2017 ($TESHI^{PR}_{2017}$). The darker the orange, the greater social hardship is implied. The top map assumes equally weighted responses ($w_{1\ldots,4}$ = 0.25, or Suicides, Excess Mortality, Median House Prices, and Employment, respectively); the middle map assumes death-related responses as equally weighted ($w_{1,2}$ = 0.5, $w_{3,4}$ = 0); and the lower map assumes that $w_{1,2}$ = 0.4 and $w_{3,4}$ = 0.1 to illustrate the implications of value-based weighting schemes, and how the distributions of the *TESHI* can subsequently vary.

Leveraging data developed by a treatment-effect model, a novel and adaptable method was proposed to develop a Social Hardship Index based on geographic units exposed to an intervention. In this case, the geographic units are municipalities that proxy the people in Puerto Rico who are exposed to the intervention, Hurricane Maria in 2017. Several limitations were incurred due to data availability and quality. For instance, some of the index values were based on backcasting techniques to fit a significant model because of the scarcity of time point observations for some variables (i.e., datasets with sparse vintages). In the future, the performance of the model can be improved, and subsequently, the accuracy of the *TESHI*. For example, the number of observations can be expanded to include a more comprehensive set of predictors, or instrumental variables can be identified.

A potential extension of the methodology was demonstrated to develop a Treatment-Effect composite Social Hardship Index (*TESHI*). The *TESHI* was built according to each of the response variables for each of the 78 municipalities in Puerto Rico. These four subsequent sub-indices illuminate the landscape of vulnerability in Puerto Rico in terms of three human dimensions of disaster hardships (psychological, demographic, and economic), the social drivers behind these hardships, and how the vulnerability landscape may change over time. Moreover, the *TESHI* explicitly ties the role of climatic hazards like Hurricane Maria to the emergence of vulnerability and human suffering. These results reinforce the importance of human-centered impacts that go beyond economic outcomes, such as the psychological and demographic outcomes shown here.

In terms of the proposed framework for social hardship, future work can leverage the *TESHI* approach for novel cases or refine the choice of scale and unit of analysis. The *TESHI* methodology is adaptable to alternative spatial or administrative units for analysis at scales that fit the needs of researchers and stakeholders. For example, the index may be calculated per county or neighborhood district. Given data availability, the *TESHI* can include a more comprehensive set of response variables among the four dimensions used to frame human impacts due to disasters (psychological, demographic, economic, political). Impacts manifesting in the psychological and political dimensions, for example, are particularly challenging to include due to limitations in data collection and availability.

Future work can address the challenge of developing a social hardship metric as a composite of response variables for a broad view of vulnerability and the subsequent question of how to weigh the response variables. Weighting schemes at the level of outcomes are difficult because the components to be weighted are value-based outcomes, such as mortality, mental health, and employment. For these reasons, weighting is often addressed by way of expert opinion and policymaker choices. One potential pathway would be to group outcomes by intensity, such as suicides and excess mortality, in a dynamic framework that allows decision-makers to observe SHI outputs based on different sets of outcomes. Furthermore, social hardship can have many manifestations along human dimensions that go beyond the set introduced here, and those outcomes of value can be identified by stakeholders and policymakers aiming to reduce disaster impacts.

Regardless of the choice in weightings, some factors may have a consistent impact across social hardship outcomes, and quantitative methods exist to explore these trends. In terms of composite indices, OECD (2017) highlights the use of Monte Carlo techniques for sensitivity analysis of different sub-index weighting options. Xun and Yuan (2021) leveraged Monte Carlo methods to assess the sensitivity of different weightings for a set of urban resilience indices on specific outcomes. Using such methods for weighting responses could illuminate which weights for which responses have the greatest effect on bottom-line results. In turn, Monte Carlo methods can help analysts and decision-makers alleviate the dependence of resilience assessment on assessor preferences and yield less subjective weights for each outcome (i.e., index response variable). Alternatively, multi-criteria decision analysis (MCDA) has been leveraged to quantitatively weight aggregate indicators. For example, McIntosh and Becker (2020) worked together with in-practice experts and used an MCDA method to generate weights for a subset of expert-selected indicators of seaport exposure and sensitivity to climate and extreme weather. The advantages of MCDA include its transparency in terms of valuing outcomes, insights into different judgments of value, and capability for comparison of trade-offs between different choices during the decision-making process.

It is important to note that the *TESHI* framework aims to isolate the outcomes or realizations of vulnerability, here termed social hardship, due to a specific disaster. This framing differs conceptually from other quantitative frameworks for disaster indices that focus more on the precedent sociological structures of vulnerability or seek a hazard-agnostic index (Johansen et al., 2017). On the one hand, the advantage of the *TESHI* is the direct account for the burdens that people have faced as an outcome of a past disaster using objective responses. On the other, the *TESHI* is less applicable in terms of general hazards vulnerability. Social vulnerability, especially in general respect to environmental hazards, is a complex and continuously evolving property of communities that is difficult to capture in a single metric (Carvalhaes et al., 2021). In this sense, the *TESHI* is a proper metric when interpreted specifically to adverse human outcomes of Hurricane Maria, and can be further generalized in interpretation by combining observations of several hurricane events in a locality.

The disaster-level specificity and adaptability of the proposed methodology are central to the broader research implications of this work. The Treatment-Effect models and the *SHI* composites can be applied to other contexts using human-oriented response variables identified by local researchers and stakeholders, thus enabling isolated communities to better address and mitigate the human hardships that come with disasters. The *TESHI* produced should be interpreted in terms of vulnerability to Hurricane Maria, or in terms of future hurricanes of similar magnitude. Maria was a category 5 hurricane with winds up to 155mph (Pasch et al., 2019), representing an extreme event with a certain and relatively high level of impact. Considering the historical hurricane risks of the Caribbean region along with climate change, it can be expected that Puerto Rico will likely cope with hazards of similar intensity as Maria in the future. The *TESHI* can also be applied to infrastructure models that couple social and technical considerations to include social outcomes as objectives for optimal infrastructure recovery and robustness when resources are scarce (Boyle et al., 2021; Karakoc et al., 2019). Integrating social considerations in the form of objective metrics can support the development of planning tools and infrastructure simulations that help identify effective strategies to reduce human hardships in the face of oncoming future climate hazards.

In terms of the broader societal meaning of this study, the proposed Treatment-Effect methodology and indices can enable science-driven tools that support disaster risk reduction and sustainable development. Toward achieving sustainable development goals (SDG), including eradicating poverty, supporting good health and wellbeing, reducing inequality, and taking climate action to combat climate-related impacts, it is essential to have methods available to tackle social hardships directly. Our framework can be used to address climate-related hazards to the sustainability of livelihoods, or go beyond monetary and economic considerations to capture aspects of human suffering, such as depression and anxiety. Focusing on human outcomes of social hardships can enable decision-makers to prioritize and allocate critical resources that mitigate the factors that cause distress and degrade the sustainability of livelihoods for the most vulnerable. For isolated places like Puerto Rico, infrastructure recovery and emergency response can be driven by social vulnerability and the reduction of human hardships.

2.4 Toward Social Functions for Power Network Simulations

The *TESHI* method above addresses the limitations of static indices that represent a snapshot of the social structures assumed to make populations vulnerable. By leveraging panel data and computing a series of annual sub-indices, *TESHI* makes it possible to observe social vulnerability as dynamic through time. Secondly, the *TESHI* ties realized vulnerability to specific disastrous events. In the case presented here, Maria represents a specific hazard, and at the same time, it marks a type of hazard of a relative intensity (i.e., a category 5 hurricane in Puerto Rico).

However, the method is not directly tied to service losses due to power network failure. Furthermore, it is important to note that power outages are not momentous events but rather persist for a length of time as infrastructure is recovering. At the aggregate level, such as a municipality, communities must endure both the proportion of services loss and the time to full recovery. For example, there is a difference in social hardship if the power network service for a municipality is reduced to 30% functioning versus 50%

functioning in respect to the normal operating performance of the power system. Likewise, the longer it takes for services to return, the greater communities will have to cope and adapt without infrastructure services.

Geospatially oriented indices like SoVI address the spatial heterogeneity of social vulnerability, and *TESHI* helps address the vulnerability changes over time and is realized upon a hazard. However, the temporal dimension is yet to be captured in terms of vulnerability dynamics relative to the duration of infrastructure disruption and recovery. To further advance models that capture the dynamics of social vulnerability, it is, therefore, necessary to move toward social functions rather than social metrics toward socio-technical infrastructure resilience simulations. A social function outputs a measure of social hardship as a function of the level of infrastructure service loss due to a disruption like a hurricane, and the service levels of service over time as infrastructure recovers.

A recent example of emerging social functions for infrastructure resilience and reliability has been presented by Esmalian et al. (2020). Using an alternative statistical framework (e.g., Kaplan-Meier Curves), the study developed an empirical approach toward identifying logistic functions for household tolerance to sustained lack of critical infrastructure services like power (termed “susceptibility”). The study relies on subjective field data by polling groups of people (with known demographics and other social-economic variable data) who have recently experienced hardship from climatic hazards leading to service disruptions. The individuals rate their experienced hardship on a categorical scale (i.e., categorical response variables), responses are coded, and a model is fit to the data. However, the reliance on self-reported data is a common and inherent limitation in capturing the human dimensions of disaster impacts.

Whereas social indices may be more appropriate as “yard stick” tools for planning purposes or identification of communities and types of resources that may need attention to improve resilience or reduce vulnerability, social functions can better capture the cumulative hardship that is endured by communities relying on critical infrastructure services that take time to recover. Several benefits are available with social functions.

First, infrastructure failure and recovery models can better capture the time-dependent nature of social dynamics in respect to the duration of infrastructure service loss or the intensity of natural hazards. In this way, the cumulative social hardship in respect to the level and duration of service disruption or hazard intensity and identification of thresholds for human tolerance in terms of negative outcomes can be quantified (e.g., suicides, economic collapse). Furthermore, critical thresholds can be identified in terms of human tolerances for infrastructure service loss, such as the duration at which outcomes of social hardship are realized (e.g., loss of critical functions like refrigeration of medicines, heat stress, mental health outcomes). Secondly, more accurate estimates of social hardships can be developed based on the properties of the socio-technical network (e.g., electrical system topology, the spatial distribution of social vulnerability). Leveraging the various properties of socio-technical networks from an infrastructure service perspective, future hazards can be modeled in accordance with hazard and infrastructure design scenarios, and various mitigation policies can be explored (e.g., changes in topology, strategic redundancies).

CHAPTER 3

SOCIAL VULNERABILITY AND COMMUNITY RESILIENCE INDICATORS IN THE FACE OF COMPLEXITY

3.1 Introduction

As society continues to evolve, interacting networks of people, objects, and systems within economic, technological, social, and ecological dimensions are becoming increasingly interdependent (Heylighen et al., 2006). Urban systems, the interconnected combinations of infrastructure like power, water and waste systems, along with the social organization and institutions that altogether make up and govern an urban area like a city or region, are likewise interdependent, dynamic, and constantly evolving (Gershenson, 2014; McPhearson et al., 2016). Complex Adaptive Systems (CAS) are characterized by interactive heterogenous networks where a change in one component can affect changes in other components such that structures, processes, and organization emerge from their interactions (e.g., the ability of community to recover and adapt to future disasters arising from strong and weak social ties among diverse actors in response to a flood). Such emergent phenomena include resilience, the structural flexibility to adapt and learn when the unforeseen happens. An urban system as a CAS is further characterized by being very difficult to predict or understand its inner workings by dissection of individual system components (i.e., the sum is greater than the parts). Theoretical perspectives of the urban space that embrace this view are becoming more widely recognized among resilience-related fields (Coetzee et al., 2016; Folke, 2006; Martin-Breen & Anderies, 2011; Meerow et al., 2016).

As the interrelationships among social, ecological, and technological systems (i.e., urban dimensions) are becoming recognized, disaster resilience index (DRI) methods are becoming increasingly comprehensive, yet are not necessarily based on CAS concepts (see sections 3.3-5). The variety of approaches and variables across urban dimensions suggests that index development faces overwhelming challenges and may be inadvertently substituting for an understanding of urban systems as CAS. While efforts to develop DRI aim to justify and guide resilience investments, it has been argued that the complexity inherent in urban systems is not being captured by these methods (Eakin et al., 2018; Koliou et al., 2018a). If key complexity concepts are overlooked, and research and development of indices are misguided toward increasingly sophisticated but tangential methodologies, attempts to make communities resilient would be futile. In turn, adaptation efforts may not pay off and the case for investing in resilience may be undermined. Resulting interventions can either neglect or undermine resilience capacities, and unintended trade-offs can further compromise communities. Despite the popularity and practicality of DRI, the reduction of an urban system to a set of quantitative indicators runs the risk of sunken investments and maladaptation that can compromise the resilience of future cities (Barnett et al., 2008; Magnan et al., 2016).

Given the concurrent trends of growing recognition of complexity and the prominence of composite indices, an understanding of how current methodologies and variable selection fail to capture the complex properties of an urban system would result in more effective decision-making. Complexity-oriented development and application of resilience indices can provide a way to profile resilience capacities, augment DRI with complexity-related methods, and develop system-oriented enhancements (e.g., social connectivity) in dealing with future urban and climatic uncertainties. In order to enhance urban resilience to reduce human and economic losses in the face of climate change, socio-technological evolution, and a non-stationary future due to surprise events, it is imperative to provide city planners and managers a way of determining actionable yet pragmatic indicators, such as those that can be leveraged from data, in maps, engineering and decision models (Biggs et al., 2011; Reddy & Allenby, 2020).

3.2 Objectives and Scope

Several publications provide literature reviews of the current landscape of resilience indicators, respective methodologies, and major concepts for composite index design (e.g., Asadzadeh et al., 2017; Beccari, 2016; Reddy 2020). However, these works stem from disparate perspectives, and although complexity is sometimes mentioned, they do not systematically apply a CAS lens. The overarching aim in this paper is twofold (Fig. 3.1): to first synthesize established literature on CAS and resilience of urban systems (sections 3.3-5), and secondly, to draw subsequent connections between commonly used DRI indicators and generally accepted properties or tenets of resilience and CAS (sections 3.6-7). The specific objectives listed below are meant to aid researchers, planners, and decision-makers to acquire a different perspective into resilience of urban systems in terms of conceptualizing and integrating complexity into well-known tools (i.e., DRI):

(i) Provide a background and synthesis of the literature at the nexus of disaster risk, urban systems, socio-ecological resilience, and complexity.

(ii) Characterize major trends in indicator selection for composite index development based on a meta-review of established review articles that discuss indicator selection for multi-dimensional (i.e., social, institutional, infrastructure, etc.) composite disaster resilience indices (DRI).

(iii) Outline the capabilities of DRI and respective indicators to capture properties of CAS, identify deficiencies in this regard, and discuss routes toward improving DRI from a complexity perspective.

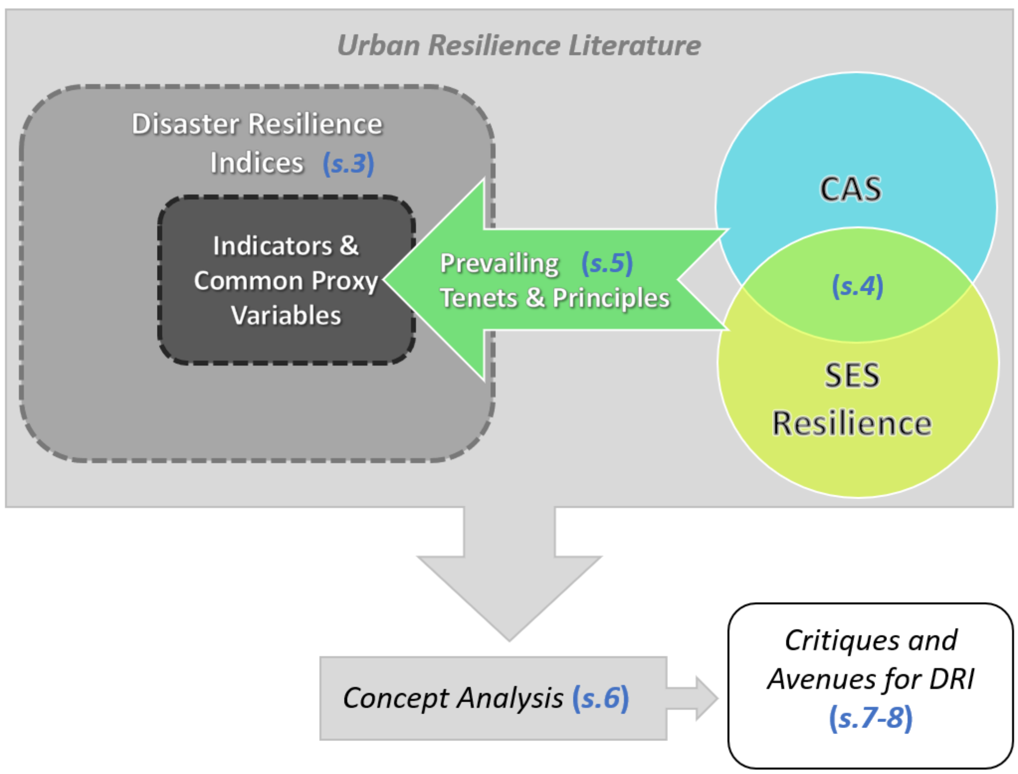

Figure 3.1. Conceptual diagram illustrating the objectives, approach, and contribution of this paper towards identifying composite disaster resilience indices (DRI). Complex Adaptive Systems (CAS) and Socio-ecological Systems (SES) literature is reviewed to identify prevailing tenets and principles that can be used to conceptually analyze typical choices for resilience indicators and proxy variables. Numbers in blue correspond to which sections of the manuscript each component is covered (e.g., "s.3" means DRI are discussed in section 3.3).

The analytical framework is first addressed via a brief meta-analysis of the literature on resilience indices (section 3.3), followed by contextualizing urban infrastructure and resilience in terms of CAS (section 3.4). Sections 3.5 and 3.6 describe how the objectives were explored through a selection of core DRI indicators in terms of common tenets of CAS and resilience principles. This is followed by a synthesis of findings (section 3.7), and concluding with a general discussion and recommendations for further work on DRI (section 3.8).

3.3 Review of Common Approaches for Vulnerability and Resilience Indices

3.3.1 The Case for Disaster Resilience Indices (DRI)

The discourse on urban resilience has been largely driven by climate change and extreme weather, and the subsequent need to identify vulnerabilities, enhance preparedness, and develop adaptive strategies (Goldsmith & Crawford, 2014; Meerow & Mitchell, 2017; Preston, Westaway, & Yuen, 2011). Many definitions exist, but in general resilience is the ability of systems to adequately anticipate, cope with, adapt, and learn from sudden shocks like climatic disasters (more detail on resilience in section 3.4). Strategies that reduce the complexity of the structure and processes of urban systems to objective metrics, such as DRI, are attractive to urban researchers and decision-makers to develop clear, actionable insights toward making the “business case” for resilience investments and tracking progress of these measures when implemented (Cutter, 2016a; Preston, Yuen, & Westaway, 2011). Indices are relatively simple sets of numerical metrics (e.g., a value of 0 indicating very little resilience, and 1 indicating very high resilience) or categorical metrics (e.g., low-highly resilient) that can be used to compare the relative resilience status of a place-based system (e.g., community, city, county, or state) over time, or to another system (e.g., Community Disaster Resilience Index by Texas A&M, see Peacock, 2010; and the City Resilience Index by Arup, see City Resilience Framework, 2014).

Comparative metrics and well-selected indicators (however normative) empower decision-makers to take action to implement research-oriented resilience plans, by clearly identifying strong and weak areas so that resources can be efficiently allocated (Zandt et al., 2012). Community resilience metrics can enable investments toward significant economic outcomes such as lower disaster costs), more stable local economies, and enable communities, governments, and the public sector to take capacity-building actions (Bender & Benson, 2013; Cutter, 2016a; Fung & Helgeson, 2017; Rodin, 2014; Simison, 2019). As is evident in programs like the late 100 Resilient Cities, DRI enable comparisons between cities and supports research and design toward learning from disasters, developing strategies, and transferring knowledge.

3.3.2 Identifying an Established Core of DRI Indicators

To identify a set of common types of indicators, a literature search for reviews of DRI and respective indicators was performed using combinations of the key terms (Fig. 3.2): resilience, metrics, indicators, measurement, composite, indicators, indices, disaster, climate, and review[5]. Google Scholar was used as the search engine because of its wide

[5] Keywords like "COVID-19" or "pandemic" were excluded because these events were still too recent and underdeveloped.

accessibility, links to articles hosted in multiple databases, and does not favor a particular group of publishing outlets (Fekete, 2019). Several articles published after 2015 cite previous reviews, so articles older than 2016 were excluded. Results were further filtered for peer-reviewed publications with at least a partial focus on quantitative indicators specific to resilience of urban systems to natural and general hazards, as opposed to vulnerability, risk, or resilience to other phenomena. Reviews considering only a single dimension of urban systems were excluded, such as those focusing only on the social domain or general social resilience. However, community resilience reviews were retained when they considered multiple dimensions of urban systems in respect to a community, such as infrastructure assets.

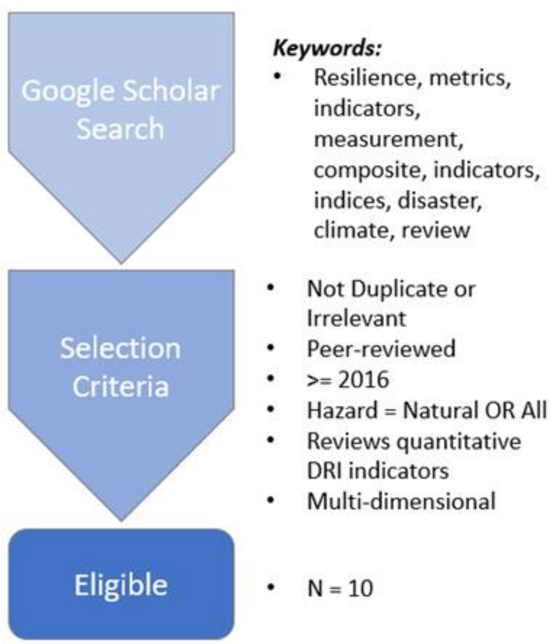

Figure 3.2. Summary of the literature search method adopted to identify papers reviewing common and established DRI indicators.

Table 3.1 lists the ten review articles that were ultimately selected, which summarize and evaluate the state of DRI using various approaches including bibliometric[6] and qualitative literature analysis (Beccari, 2016; Cai et al., 2018; Cariolet et al., 2019, Rus et al., 2018), case study compilation and analysis of existing index frameworks (Asadzadeh et al., 2017; Cutter, 2016a; Sharifi, 2016; Parsons et al., 2016), and conceptual analyses of current research progress that includes DRI (Johansen et al., 2017; Koliou et al., 2018). Syntheses from these reviews include highlighting theoretical perspectives, dominant dimensions of resilience (e.g., economic, institutional), and trends regarding methodological choices for DRI.

[6] Bibliometrics is the use of statistical methods to analyze books, articles and other publications.

Table 3.1. Selected articles that review literature and compilations of disaster resilience indicators and indices.

Authors	Description of the Type of Application and Index framework Proposed
Asadzadeh et al (2017)	• No list of persistent concepts or variables compiled, but rather focuses on dimensions and methodological choices. • Proposed eight-step procedure for composite indicator building. • Recognizes increasing complexity in community resilience and distinguishes resilience in terms of socio-ecological and engineering perspectives.
Beccari (2016)	• Comprehensive bibliometric review of vulnerability, resilience, risk composite indicator methods. • Includes list of dominant variables and concepts from the literature. • Concludes that deductive, quantitative and mappable methods are dominant.
Cai et al., 2018	• Systematically analyzes 174 scholarly articles related to resilience measurement using content analysis and review tables in terms of definitions of resilience, approaches to resilience measurement, most commonly adopted indicators, and proposed adaptation strategies. • Tabulates most frequently used resilience indicators in rank order and by the top disaster types found in the systematic analysis.
Cariolet et al (2019)	• No list of common concepts but includes a detailed discussion of variable choices. • Critiques resilience indicator methods and composites as too simplistic and suggests hybrid methods to better capture complexity of resilience.
Cutter (2016)	• Evaluates 27 DRI and approaches in terms of theory, spatial characteristics, methods, and resilience domains (e.g., community, economic). • Concludes that there is no dominant framework but lists common core concepts, measurements, and prevailing proxy variables.
Johansen et al (2017)	• Focused on social resilience, but does include multiple resilience dimensions. • Classifies metrics as community-based, sociological, or sector-specific, and reviews methodological choices between these three categories.
Koliou et al (2018)	• Broad overview of the state of research on resilience dimensions across disciplines. • Reviews community resilience initiatives on international, national, regional, and local levels, including infrastructure domains and essential lifelines.

	• Calls for research regarding integration of system of systems, characterization of community-built environment, critical infrastructure interdependence, social complexity at multiple scales, and coupling engineering, economics, and social science models.
Parsons et al (2016)	• Includes a brief survey of index landscape and presents framework, themes, and indicator selection for Australian Natural Disaster Resilience Index (ANDRI). • ANDRI synthesizes concepts and variables from the survey, with a greater focus on capacities and inclusion of less common variables such as learning.
Rus et al (2018)	• Reviews resilience and respective sub-components from complex urban system and seismic risk perspective across four dimensions: technical, organizational, social, and economic. • Integrates physical and social components of an urban system and highlights necessity to capture interactions (e.g., such as in a network or graph theoretical approach).
Sharifi (2016)	• Reviews 36 resilience frameworks in terms of resilience dimensions, scales, temporal dynamics, methods, and applications. • Concludes that ecological dimension is often under-represented and a comprehensive model that includes all resilience criteria is lacking.

Regarding the overall capacities that resilience metrics should indicate, Beccari (2016), Cai et al. (2018), Cutter (2016a), Parsons et al. (2016)[7], and Sharifi (2016) list some of the persistent indicators adopted across methodologies. The most widely cited of the selected articles, Cutter (2016a) presents a measurement core for disaster resilience with proxy variables that are commonly found in publicly available data based on a review of established indicators and methods, and categorizes them as assets or capacities for resilience (Table 3.2). This core largely aligns with the other review listing persistent indicator criteria (particularly Beccari, 2016 and Cai et al., 2018, though the latter does not include indicators in the environmental domain).Therefore, the following analysis

[7] Presented as a list of indicators chosen for the Australian Natural Disaster Resilience Index based on a literature review.

leverages this core of indicator concepts and proxy variables for analysis against essential tenets of complexity and principles of SES. This set is not intended as an exhaustive list of concepts and indicators, but rather as a representative set to demonstrate how common approaches for resilience indicator selection aligns with fundamental CAS and SES resilience perspectives. However, indicators and proxy variables from the other reviews were sometimes noted for comparison or as additional examples.

Table 3.2. Persistent variables for community disaster resilience (right column; as interpreted from Cutter, 2016a) based on assets (resources that can be leveraged upon disasters) and capacities (capabilities that emerge upon disasters) (left column).

Domains and Capacities for Resilience Indicators	**Common Types of Proxy Variables**
Community assets and functions	Community services (number)
Connectivity	Feeling of belonging to the community' proximity to urban areas
Economic	Income
Emergency mgmt.	Shelters, evacuation routes
Environmental	Impervious surfaces
Infrastructure	Buildings of various types (emergency, government, power, bridges, commercial)
Information/communication	Prior recovery, hazard severity
Institutional	Mitigation plans (% covered)
Social	Educational attainment
Social Capital	Civic organizations; religious

3.3.3 General Takeaways from the Selected Articles

While there are only partial overlaps between reviews in Table 3.1 due to varying scope, methodology, and framings, there is agreement among certain critiques and conclusions. Generally, quantitative top-down methods (e.g., relying on aggregate datasets rather than than field data) are tremendously popular, especially if amenable to geographic visualization (e.g., DRI-enabled decision tools like GeoApps). Indicators can be classified into two general domains of resilience, (i) assets or capital, and (ii) capacities and governance. Holistic indices that aim to be hazard-agnostic suffer generalization and contextual limitations. Validation (i.e, internal and external validation, cross-validation, uncertainty and sensitivity analysis, ground truthing) remains a persistent problem and is sometimes entirely ignored in indicator frameworks. The prominence of insufficient validation and uncertainty analysis and their importance has been noted for social vulnerability indices (SVI) and DRI, with suggestions that leverage statistical methods (e.g., using "revealed vulnerability" data like human loss or satisfaction with damage compensation) and cross-validation with alternative studies (Fekete, 2019; Tate, 2013). Lastly, interactions between urban system components and subsystems remain a necessary but difficult area for research, development, and coupled methods or interdisciplinary pursuits.

3.4 Contextualizing CAS and Urban Resilience

"The complexity turn"[8] has influenced several research fields interested in urban resilience to climatic disasters, such as disaster risk reduction, urban geography, and resilience engineering and management, into framing cities as complex systems (Allenby & Chester, 2018; Castellani, 2014; Cutter, 2016a; Folke, 2006; Meerow & Newell, 2016; Reddy, 2020; Urry, 2005). Seminal publications paving the way for this turn stem from ecology, particularly the resilience of ecological systems framework by Holling (1973; 2001). Ecological perspectives view CAS as composed of holons (hierarchical levels or subsystems with subjective boundaries where information and materials are gated and transferred; Kay, 2008) that are nested in a panarchy (holons exist

[8] The recognition of complexity as inherent and unavoidable in human and other systems.

as hierarchical series of adaptive cycles, and both top-down and bottom-up controls between holons drive resilience and evolution) (Gunderson, 2019). Resilience is framed as an emergent property of CAS, which as an interconnected whole, can absorb change, reorganize, or transform while maintaining major functions and an essential identity (Walker et al., 2004).

Resilience as coping with change and perturbations has since been adapted into engineering for critical infrastructure systems (CIS) services (Comes & de Walle, 2014; Hollnagel et al., 2006; Woods, 2015; Reddy, 2020), and research on the built environment as SES and socio-technical systems (STS) (Anderies, 2014; Markolf et al., 2018; Pelling & High, 2005; Smith & Sterling, 2010). In terms of seismic community resilience, Bruneau et al (2003) present four key properties of resilience in both physical and social systems ("4 R's" o resilience): Robustness (i.e., strength or hardness against degradation or function loss), redundancy (extent of substitutable elements or systems), resourcefulness (capacity for identifying problems, prioritizing, and mobilizing resources), and rapidity (timeliness in meeting goals after disruption). Reddy (2020) proposed five main sub-attributes from a techno-centric viewpoint: (i) Preparedeness, the ability to anticipate and proactively invest in adaptation strategies; (ii) Robustness, or the ability to withstand sudden shocks and provide the service it has been designed for; (iii) restructurability, or the flexibility to reorganize so as to maintain at least partial functioning; (iv) restorativity (rebounding), the ability to recover functions in a timely manner and without excessive losses; and (v) adaptivity, the ability to learn from failure and adversity and to incorporate changes that improve the ability of systems to handle similar events in the future.

Some engineering-oriented attributes, like robustness, are conceptually the inverse of vulnerability (sensitivity to damage or loss upon exposure). While it is reasonable to view robustness as a component of resilience, this paper aims to distinguish attributes of resilience from vulnerability, taking on the perspective that urban systems are always vulnerable in some form, so it is salient to focus on attributes that relate to the flexibility, agility, and persistence of a CAS. Resilience centered on flexibility and CAS capacities better align with CIS as panarchies in terms of vulnerability paths and "creative destruction" (Pescaroli & Alexander, 2016), and with STS perspectives that put transformation at the core of resilience of human-technological systems (Amir & Kant, 2018). In this way, urban systems are like ecological systems that display complex interconnections and nested cycles of evolutionary adaptation (Janssen, 2001; Pandit et al., 2017).

SES perspectives traditionally leverage complexity-driven concepts and frameworks like adaptive cycles for ecosystems and society as interconnected subsystems, but theoretical frameworks have extended them to the built environment and urban resilience. Principles of resilience for ecosystem services have been proposed which include diversity, redundancy, connectivity, polycentricity, slow variables and feedbacks, understanding of CAS, learning and participation (Table 3.3; Biggs et al., 2012, 2015; Folke et al., 2016; Wiese, 2016). SES perspectives that include coupled infrastructure have proposed partially overlapping principles that more directly acknowledge the built environment (e.g., Anderies, 2014; Suarez et al., 2019). Such principles highlight systemic properties that can be monitored, measured, and leveraged to enhance resilience of urban systems. These perspectives highlight CAS properties that enable resilience, while linking urban infrastructure to social dynamics, ecological interactions, and technological evolution entangled in a complex system. Therefore, these SES resilience principles represent key concepts for CAS (section 3.5), and are the basis of our analysis in section 3.6.

Table 3.3. Resilience principles for complex systems from the socio-ecological perspective (based on Biggs et al., 2012; 2015; Folke et al., 2016; Wiese, 2016).

Resilience Principle	**Description**
Connectivity	The extent to which paths and degrees are present for resource and information flows and interactions across socio-ecological landscapes.
Diversity & Redundancy	Diversity refers to the variety of elements, balance in the quantities of each element, disparity between elements, and heterogeneous distribution. Redundancy refers to the replication of elements or functions in a system that can ensure that some elements compensate for the loss of others (i.e., opposite of disparity).
Learning and Experimentation	The processes of developing knowledge, behaviors, skills, values, and preferences at individual, group, and societal levels within an SES.
Participation	Active engagement of relevant stakeholders in the governance and management of SES.
Polycentricity	A governance system composed of multiple centers of decision making nested at different scales.
Slow Variables & Feedbacks	Variables with slow rates of change as to often be considered constant, but has the potential for feedback and the surpassing of critical thresholds.
Understanding of CAS	A mental model or cognitive framework characterized by the acknowledgement of unpredictability, emergent macroscale behaviors, continuous evolution, responsive adaptation, and uncertainty pervasive in SES.

The coupling of multiple complex and heterogeneous systems has greatly compounded the complexity in urban systems, making resilience to disasters difficult to measure, manage, and predict. Challenges have been noted, including those highlighting deep uncertainty (where probabilities of possible futures are too difficult or impossible to rank) and wicked complexity that requires fundamentally new approaches to how we function (Allenby & Chester, 2018; Chester & Allenby, 2019; Haasnoot et al., 2013; Hallegatte & Engle, 2012; Walker et al., 2013). Part of this wickedness and uncertainty has to do with infrastructure as embedded in rapidly coevolving technological and social systems in the Anthropocene, the geological age when humans dominantly drive the Earth system and accelerating change drives high levels of unpredictability (Allenby & Chester, 2018; Chester & Allenby, 2019; Markolf et al., 2018). The challenge for disaster resilience and established DRI is merging what was traditionally thought of as natural disasters into what is now being conceptualized as a highly interconnected and unpredictable, yet human-driven Earth system.

Anthropocene perspectives increasingly underscore the irreducible complexity of social dynamics. Human agency, conscience, and societal values, along with technological dominance, introduce subjective interactions into coupled systems that effect how these CAS self-organize. Human cognition, relative to technical and ecological systems, makes coupled systems asymmetrical – that is, dominated by the social domain where collective choices and sociopolitical forces govern how urban systems adapt (Manuel-Navarrete, 2015). Eakin and colleagues (2017) argue for the complexities of sociopolitical infrastructure such as formal and informal rules are necessary for urban resilience thinking. The call for the inclusion of highly complex social dynamics also characterizes how urban resilience is being conceptualized, and forms the basis of criticism by some social scientists that DRI are too-reductive, normative, context-dependent, and static (Béné et al., 2014; Eakin et al, 2018).

3.5 Resilience Principles and the Tenets of CAS

3.5.1 Finding a Core Set of Essential CAS and Resilience Attributes

As efforts to frame urban resilience are converging around CAS, traditional approaches for understanding urban systems and preparing for the future are inadequate , and a turn toward systems thinking is necessary (Ahern, 2011; Biggs et al., 2015; Cote & Nightingale, 2012; Folke et al., 2010; Walker & Salt, 2012; Xu et al., 2015). There are many branches in the history of the complexity sciences that evolved in parallel and sometimes interlink (e.g., general systems theory, cybernetics), so an exhaustive treatment of this history is beyond the scope of this paper[9]. However, there are some commonly accepted essential tenets of CAS. In a recent review of complexity theory, Turner and Baker (2019) outline the many definitions of CAS and respective characteristics, and propose a set of "tenets" of CAS (Table 3.4.).

Some tenets are closely related or interdependent allowing them to be bundled together. For instance, since path dependence was explained in terms of sensitivity to initial system conditions or history, the three tenets are consolidated into "sensitivity to initial conditions". Other systems characteristics describing the essential tenets can be similarly handled. For example, uncertainty in complex systems was incorporated into the property of irreducibility because any system representation is necessarily a limited and biased manifestation of the "actual" system so that subsequent indicators involving "uncertainty" in some manner (Allenby, 2012; Cilliers, 2002).

[9] See Castellani (2014) for an exceptional review on the historical evolution of the complexity sciences.

Table 3.4. The link proposed in this paper between important tenets of complex adaptive systems (CAS) and different characteristics of socio-ecological systems (SES) resilience.

CAS Tenets	**Description**	**Most Closely Related Resilience Principle**
Adaptivity	Systems respond to and affect external environments and reconfigure to meet changing demands (i.e., systems adapt and evolve).	Diversity & Redundancy
Emergence	Synergistic outcomes from the interactions of several heterogenous components that spontaneously interact to form patterns (i.e., *self-organize*) that cannot be deduced by dissecting attributes of any one individual component (i.e., "The whole is greater than the sum of the parts").	Connectivity, Polycentricity
Irreducibility	Characterized by inherently partial system framings (i.e., "Whole system ignorance'), uncertainty and unpredictability of system outcomes.	Understanding of CAS, Participation
Operates between Order and Chaos	Systems can experience spontaneous self-organization and emergent order (i.e., innovation and new structures emerge at "at the edge of chaos").	Learning & Experimentation
System History	Systems have *non-linear* relationships among variables in time, and future conditions are *path-dependent* (i.e., limited by previous paths and conditions). Systems exhibit a *sensitivity to initial conditions* so that small differences can produce widely different outcomes and dynamics over time, while slow variables can unexpectedly approach critical thresholds.	Slow variables & feedbacks

Resilience emerges from systemic interactions occurring before, during, and after disturbances, where the tenets of CAS and SES resilience principles come into play to support adaptation, learning, and the "bouncing back" of urban systems. For example, connectivity and polycentricity can facilitate the ability for an urban CAS to self-organize; diversity and redundancy enable adaptivity; slow variables and feedbacks are linked to non-linear patterns and the history of the system; the irreducibility of CAS require an understanding of CAS and participation; learning and experimentation speak to the possibility of re-ordering after unforeseen consequences (Anderies, 2014; Coetzee et al., 2016; Levin et al., 2013).

It is important to note that many CAS discussions arise out of non-agent or socially agnostic systems, and in-turn, downplay or overlook the role of human elements (e.g., institutional structure, leadership). Equity, for one, is the most difficult resilience principle to relate to the tenets as it is normally based on a call for justice (i.e., resilience for whom). That equity relates to irreducibility and systems thinking is here justified in terms of the "5 W's" of resilience (resilience for what, whom, where, why and when), which stifle the framing of an urban system as generally resilient without potential trade-offs or winners and losers (Cretney, 2014; Cutter, 2016b; Meerow & Newell, 2016). Equity is further related to irreducibility and systems thinking in terms of Edwards' (2009) four "E's" of resilience which highlight the limited role of centralized planning or definitive templates for building resilience in the social domain: Engagement (strategies based on dialogue and feedback), education (as embedded in daily lives in any form), empowerment (assumes communities have relevant experience and should be given tools and resources to act), and encouragement (communities are encouraged to play a role by both formal and informal institutions).

In this way, CAS tenets and SES resilience principles can be distinct, yet related. This paper does not view these tenets and principles as absolute and universal, but rather as the outcome of a synthesis of how Anthropocene challenges like urban resilience to more frequent and intense climatic shocks are being framed. CAS tenets and SES resilience principles are leveraged in for analysis in section 3.4 to guide reflections on common types of resilience indicators, and DRI applications. However, it is important to note that the nature of urban resilience as a CAS presents major limitations and assumptions that challenge the generalization and application of DRI (Rus et al., 2018).

3.5.2 Misalignments Between Established DRI and CAS

While index methods aim to reduce urban resilience to a set of capitals and capacities for an overall measurement of resilience, CAS research tends to focus on unearthing the dynamics and spatiotemporal patterns within a system that lead to the emergence of resilience. Common examples are process-oriented and multi-agent models where networked agents or components interact to produce macro-level trends or transitions in state variables (Costanza et al., 1993; Miller & Page, 2007; Tsvetovat & Carley, 2004). Such models are meant to map the dynamics of systems and can indicate the potential for a system to self-organize and adapt to perturbations. Metrics associated with these approaches are often topological or pertain to the potential for interaction, such as the number of links that connect to a given node (degree of a node), or network density, the ratio between the number of connections to the number of possible connections (Thurner et al., 2018). In terms of resilience, computational models seek to determine points of criticality where interactions tip the system toward transitioning to a different state that can be either desired or undesired (Miller & Page, 2007; Thurner et al., 2018). Macro-level metrics are sometimes sought, such as a high-level metric for self-organization of a CAS by King & Peterson (2018).

It is important to point out that composite indices may be categorically misaligned with CAS theory due to their common framing of resilience as representable by a sum of quantified parts, whereas complexity assumes synergistic effects between many autonomous interacting parts, which can be unpredictable or novel. Composite index methodologies implicitly assume a “simple” system in that a selection of quantifiable subsystems corresponds meaningfully to how urban systems behave upon disasters. This misalignment occurs methodologically when indicators are added up and assumed to indicate some ordinal level of resilience, but also conceptually when variables are assumed to be meaningful, consistent, and generalizable from one event to another, and among different and continuously evolving urban systems.

Approaches and epistemological assumptions between DRI and CAS-oriented methods may be fundamentally different, but they can still be viewed as either complementary to each other, or as a way to transition between dynamic models and linear indicator approaches (Cai et al., 2018; Schianetz & Kavanagh, 2008). The development of sophisticated modeling of CAS can be time and resource intensive (e.g., data, modeling experts), but have been used for scenario-testing, dynamic resilience metrics, and organizational learning (Schianetz & Kavanagh, 2008; van den Belt, 2004). Indices, however, offer a clear measure and more straightforward insights pertaining to variables and resources relevant to planners and stakeholders (Butler, 1999; Zandt et al., 2012). It is recognized that the manner in which resilient performance of CAS are normally evaluated/quantified differ significantly from how index approaches measure resilience. However, to bridge the gap between these approaches this paper will focuses on how concepts and metrics used for indices broadly relate to tenets of CAS and SES resilience.

3.6 Approach for Conceptual Analysis of Resilience Indicators from a Complexity Perspective

CAS tenets and SES resilience principles are leveraged to analyze the concepts and proxy variables (i.e., resilience assets and capacities) that are dominant in DRI (as shown in Tables 1 & 2). This was done by framing a set of guiding questions. For example, to relate the common disaster resilience concepts and indicators to the self-organization and emergence tenets, guiding questions include:

i. Does the indicator capture connectivity in terms of the ability to self-organize?

ii. How is governance in terms of the ability to make decisions at multiple scales captured (i.e., polycentricity)?

While the range of methodologies is not discussed in detail in this paper, general implications of applying different methodologies are presented when relevant to a particular complexity tenet and resilience principle (e.g., choosing additive assumptions versus multiplicative or exploring more advanced techniques for a given indicator). Discussion points were developed for CAS tenets and SES resilience principles in terms of each of the common core of resilience indicators in section 3.2, including short descriptions of potential CAS significance, links to other CAS properties, and counterexamples illustrating how an indicator may be somewhat myopic in terms of complexity. Once completed, results were reviewed for general trends, significant findings, and holistic insights that may otherwise not have been captured by the piece-wise analysis. These results are described in section 3.7, followed by a broader discussion that incorporates insights from the reviewed literature (section 3.8).

3.7 Synthesis of Findings from Analysis of Core Resilience Indicators, SES Principles, and CAS Tenets

Of the indicators analyzed, social capital (bonds that communities can leverage for recovery upon disasters; Aldrich, 2010) and connectivity (linkages within and between systems; Turner and Baker, 2019) emerged as the most aligned with CAS and resilience of SES principles. However, indicators for the emergence of social capital are subject to contextual system histories (e.g., meanings or tipping points that vary from place to place), intricate trade-offs, and uncertainty toward generalizations amid evolving SES (Adger, 2003; Aldrich, 2012). In terms of connectivity, social capital proxied by the number of civic or religious organizations and adherents as indicators suggests these kinds of institutions as nodal points where individuals and communities can connect and organize to redistribute resources toward coping and recovering from a disaster.

The focus on density for all types of indicators (i.e., units per administrative boundary) can indicate the order of potentially interacting parts or the potential for functional redundancy, the latter often cited in the Table 3.1 reviews as a driving concept for indicator selection. However, focusing on proportions of a given variable tends to leave out modularity (the attribute of having components or groups of rules that act as “building blocks” that can be situationally recombined; Holland, 2006) and diversity (variety, balance, and disparity among elements; Biggs et al.,2012). While modularity may be more elusive to capture with straightforward indicators, diversity can be incorporated by methodologically shifting to data attributes that pertain to the number of different types and functions, rather than density of discrete units (e.g., number of types of religious centers, or religious pluralism rather than number of religious centers).

Ultimately, each indicator in this analysis could be critiqued for not meaningfully capturing complexity tenets in some way. This is to be expected due to the intent of resilience indicators as a reduced form or snapshot of system conditions, especially when viewed in a piece-wise fashion. Ecological and environmental factors are largely absent, which may be because such indices are normally integrated with exposure metrics, models, and tools that capture topographical, hydrological, and climatic factors. Several indicators align with complexity tenets once reframed or considered as coupled with supplementary methods.

Results describing DRI indicators according to each complexity tenet and linked SESs resilience principles (subsections) are below. Selected examples are discussed, and relatively simple modifications for better alignment with tenets and principles are noted. Higher level critiques and suggested improvements for DRI (e.g., research, development, application) are discussed in section 3.8.

3.7.1 System history – Non-linearity, slow variables, and feedbacks

Some common indicators can be framed as capturing system histories, including climate mitigation, impervious surface coverage (ISC), and previous exposure to climate hazards. Climate mitigation acknowledges emissions as a slow variable that contributes to the frequency and intensity of future potential disasters. ISC can be an insidious slow variable in terms of urbanization and urban flooding (Arnold Jr. & Gibbons, 1996; Napieralski & Carvalhaes, 2016; Shuster et al., 2005). More directly, system history is captured as previous exposure to and severity of past disasters (e.g., number of presidential disaster declarations). Places that have been resilient after a disaster likely have developed human infrastructure (i.e., experience and knowledge) and lines of information and communication capacities that can support recover and reorganization. However, a central idea of resilience is that surprise events challenge established knowledge systems and infrastructure (Aven, 2015). Nonetheless, previous disaster experience and hazard probabilities, especially if increasing in intensity and frequency through time, could indicate a greater likelihood to develop adaptive systems and prepare for the unexpected.

System history displays a minor presence in top-down composite methods. It is difficult to define, operationalize and measure slow variables and feedbacks within and between common indicators in a way that can be generalized from case to case. The potential for contextual effects can undermine basic assumptions for some indicators that assume like histories and tipping points across places. For instance, access is assumed for quantities of hospitals and disaster-relevant buildings. Considering insurance coverage and transportation connectivity as coupled with health units like hospitals may help indicate how accessible such units may be from a social and infrastructural perspective. Path dependencies and lock-ins built into communities and coupled infrastructure systems can have an impact on how effective implementations based on such indicators may be to either disasters or coming changes (Berkhout, 2002; Chester & Allenby, 2018). For instance, a place may have many emergency buildings that are vulnerable due to construction age and low investment in maintenance. Such interdependencies between indicators are often stressed as a next step for DRI in the literature reviewed (Table 3.1).

Quantitatively, slow variables can be captured as rates, limits, and thresholds (i.e., tipping points) of common indicators. Rather than proportion, the rate of development using a series of ISC data can indicate the approach to critical thresholds of development that outpace adaptation and coming environmental changes. Likewise, median income as a proxy for economic assets assumes incrementally additive units that contribute to resilience, whereas the percent below poverty assumes a quantitative leap in critical capacities, access, and vulnerabilities in the face of a disaster.

3.7.2 Emergence – Self-organization, connectivity, and polycentricity

It is difficult to explicitly link emergence to index approaches in light of the misalignments outlined in section 3.3, but indicators like the number of religious organizations framed as a proxy for the kinds of social capital that can emerge amidst disasters shows an attempt to capture the potential for desirable emergent phenomena. As related to the emergence of adaptive qualities and resilience, connectivity and organizational capacity are presented several times in reviews and index frameworks as concepts for variable selection. Connectivity indicators are usually linked to institutional/organizational assets and capacities (e.g., percent of religious adherents), or in infrastructural terms like communications (e.g., mobile or telephone access). The number of community, civic, or religious centers can be taken as a proxy for connectivity and the ability of a community to self-organize as churches and other religious centers often serve the public in need and can offer shelter, hope to recover, and guidance (Murphy, 2007). Non-profits and locally run community services may indicate social capacity for self-organizing to provide functions that are either unexpected, untrusted, or absent from other publicly provided sources (Aldrich & Meyer, 2015; Szreter & Woolcock, 2004).

Social capital is a driving concept for community resilience where indicators are used to queue for the social resources and linkages that emerge upon disasters. Volunteerism, place attachment, and civic engagement are some of the most common examples of indicators, and are captured with variables like percent of lifetime residents, proportion of voter participation, and quantities of civic engagement organizations. Community bonds, a feeling of belonging to a community, or being connected to urban infrastructure and institutions are commonly used criteria for connectivity. Other indicators of connectivity are framed around benefits of urban density, such as the proximity to critical urban services.

In terms of polycentricity, it is not clear that decision-making at multiple scales is present in the way resilience capacities are currently framed. However, since mitigation plans and activities may have implications at local, state, national, and international levels, the climate-related mitigation indicator at the community or municipal levels assume that taking part in mitigation activities along with other communities will make a difference at larger scales (i.e., local to global drivers). While the number of political districts within the spatial unit of analysis has been previously seen as political fragmentation (Cutter et al., 2010), this indicator can alternatively be framed as polycentricity where spatially-derived metrics can proxy multiple levels of decision making relative to a population or area. Using currently established indicators, spatially relating community service nodes with higher-scale disaster centers or emergency services may indicate cross-scale connectivity and polycentricity. Granted, assumptions of cooperation versus antagonism and competition may be difficult to overcome.

3.7.3 Irreducible – Understanding of CAS, participation and equity

Given that composite index schemes inherently reduce a complex situation into an operable numerical representation (Freudenberg, 2003), oversimplification and uncertainty are inherent risks. Green infrastructure (GI) can indicate multifunctional infrastructure and ISC mitigation, but GI distribution may affect equitable access to green space and related benefits, or paradoxically induce gentrification (Wolch et al., 2014). Where GI can promote resilience in one place, it can create vulnerabilities in another.

Similar is true for indicators for social capital, a “Janus-faced” concept (Aldrich, 2012). It has been found that low income communities with high rates of second-language households (two common indicators for vulnerability and low resilience), can leverage other forms social capital and even outpace wealthier communities for recovery (Leong et al., 2007). In some cases, communities tied together by a common religious organization or other common identities like race and political affiliation may exclude a minority that is left vulnerable or purposefully put in a precarious state (Aldrich & Crook, 2008).

Many reducibility issues have to do with relationships between variables that depend on space and place. A persistent issue is the effect of different units of spatial aggregation (e.g., Census tract versus county or municipalities) on how patterns emerge (i.e., the modifiable areal unit problem, Simpson's paradox). For instance, an area with a high DRI may have within it several pockets of very low DRI values that are obscured upon aggregation. In such cases, the uncertainty that arises from the choice of analytical scale is greater for generalized resilience indices and those developed for specific planning circumstances (Tate, 2013). Most index methods also assume that collections of indicators and their relationships can be generalized across geographies, such as Census tracts across a state. However, it has been shown that relationships and processes between the same set of DRI variables can differ from place to place (Chun et al., 2017; Yoon et al., 2016). Indicators also assume consistent relationships over time. Prior hazard experience assumes preparedness to known disasters. With a changing climate, disasters of unforeseen magnitudes or even types may challenge urban systems that have been resilient in the past. Infrastructure and buildings designed based on risk assessments and robustness to predicted events do not account for such an uncertain future (Gilrein et al., 2019). Mitigation plans are common proxies for disaster knowledge and resilience, but the presence of adaptive management plans may be a potential variable that can indicate CAS understanding.

3.7.4 Adaptivity – Diversity and redundancy

Several DRI indicators reflect redundancy. Examples tend toward infrastructure redundancy with indicators like the number of emergency response units (e.g., fire, police, shelters), and density of principal arterial road miles (alternative evacuation routes). Indicators tend to represent some form of capital that can absorb impacts such as economic assets (e.g., median income), rather than capacities for restructuring and adaptation like modularity or diversity. Methodological frameworks largely rely on quantities per spatial unit (e.g., city, county, tract), so it follows that many indicators can be deemed a measure of redundancy for that particular asset, or overall information, infrastructural, or organizational capacities.

A few indicators can be interpreted as capturing a degree of diversity such as the proportion employed in the primary industry or the ratio of large to small business. The latter, for instance, can potentially suggest that a large proportion of small businesses means innovation and a diversity of competitors. Redundancy and diversity of production sources, employment opportunities, and multi-skilled workers can offer functional alternatives if industries and sectors are disrupted for relatively long periods of time. Current indicators can be extended to income diversity in terms of economic markets, such as the number of active economic sectors or markets, or the percent employed across industries.

Some indicators can capture diversity or modularity if conceptually reframed and relatively simple methodological modifications are made. The number of emergency response buildings (e.g., fire, police, shelters) can be interpreted as diversity if reframed as a metric based on how many different types of functions or building types are present.

Specific measures of diversity like the Gibbs-Martin or Shannon Diversity indices can be used to indicate social diversity, or the diversity of resources, employment sectors, skillsets, and industries (Gibbs & Martin, 1962; Gotham & Campanella, 2013; Suarez et al., 2016).

3.7.5 Operating between order and chaos – Learning & Experimentation

Indicators relating to learning and experimentation include prior experience with hazards (e.g., number of disaster declarations or hazardous events), presence of adaptation and mitigation plans, and innovation (e.g., percent population employed in creative class occupations). It is assumed that prior experience with hazards proxies having learned and established improved information and communication capacities. Highly impactful disasters can materialize the unpredictability of climate events and performance of infrastructure and resilience mechanisms to a community. However, the subsequent response does not necessarily embrace safe-to-fail practices that more explicitly recognize the potential for future failures and unexpected conditions (Ahern, 2011; Chester & Allenby, 2019; Kim et al., 2017).

Resilience enhancements may be approached by investing in strengthening current systems and strategies, or by resilience thinking where more flexible and innovative systems are the focus. It is unclear if prior experience and emergency management allows for innovation and evolution toward novel and more resilient systems rather than recovering traditional and/or otherwise still vulnerable systems. An appropriate balance between robustness and flexible systems that assume unpredictability are also not described by the presence of mitigation plans/spending alone. Further, mitigation and resilience efforts facing excessively rigid institutional structures can incur maladaptive qualities like lack of organizational flexibility and innovation (McChrystal et al., 2015).

While organizational capacities like learning and coping with complexity are being recognized (Snowden & Boone, 2007; Uhl-Bien et al., 2007), it is generally difficult to find clear indicators that proxy these capacities in terms of urban resilience to climate disasters. However, indicators like the presence of adaptation and mitigation plans can be extended to the number of editions of hazard plans or adaptive management plans that suggest experimentation and rethinking of past strategies. Urban density and proximity to urban cores can provide prospects for potential indicators such as those based on knowledge spillovers, the creative economy, and innovation hubs (Bettencourt, 2013; Bettencourt & West, 2010; O'Flaherty, 2009).

3.8 Discussion

An effective index should focus on a well-selected set of key variables that indicate changes in urban system in respect to resilience (Rus et al., 2018). Considering the DRI review literature summarized in Table 3.1, it appears that in an attempt to better incorporate the complexity of urban systems, DRI approaches have annexed dimensions of urban systems (e.g., ecological, institutional) such that complexity is applied in terms of many components in many domains (e.g., social plus ecological plus infrastructure, etc.; It is important to acknowledge salient variables in all these dimensions). Such a perspective leads the process of index development to become increasingly complicated with evermore quantities of concepts and variables while overlooking critical systemic variables and dynamics (e.g., Stevenson et al., 2019 lists 66 resilience concepts originally considered for the New Zealand Resilience Index). Complexity is about more than just having many different kinds of parts, as discussed in sections 3.3-5, and excessive variables can add statistical uncertainty and bias (e.g., implicit weighting via correlated indicators; Fekete, 2019) and make validation of DRI more difficult. Avenues for improving on established research frameworks (8.1), DRI development and application (8.2), and broader implications (8.3) are discussed below.

3.8.1 Avenues for Further DRI Research toward Resilience Indices

For researchers focusing on community resilience assessment, it is important to continue distinguishing resilience from risk and vulnerability (Wisner et al, 1992), and determining how each concept applies to developing indices. Resilience remains often applied as "anti-vulnerability", with some indicators essentially adapted as the inverse of established vulnerability indicators (e.g., Cutter et al., 2010; Marzi et al., 2019). Asset-oriented indicators like income or environmentally exposed structures like mobile homes speak more to sensitivity and exposure as factors for vulnerability (Cariolet et al., 2019; Cutter, 2016b; Engle, 2011). This can be problematic since it has been shown that a community can be both vulnerable to disruption yet bounce back quickly (e.g., Leong et al., 2007), and resilience as the capacity to reorganize and restructure after a disturbance can be missed. In complexity-oriented resilience research, however, vulnerability is viewed as an integral part or even precondition for resilience (e.g., Ahern's "safe-to-fail", 2011; Anderies et al., 2006; Engle, 2011). A resilience index is less useful if it becomes a more comprehensive version of a vulnerability index, with an acknowledgement of complexity via additional dimensions for indicators. For composite resilience metrics, perhaps it is more useful a concept when framed as the capacity for reorganization after a disturbance.

Illuminating how more elusive qualities like polycentricity and self-organization can be proxied by relatively straightforward indicators is relevant for resilience researchers. In their article on disaster resilience and CAS theory, Coetzee and colleagues (2016) concluded that using CAS concepts (such as those in this paper) would enable disaster researchers to, "...analyze the dynamic changes in societal resilience profiles." There are three implications for DRI here: (1) profiling cities or communities according to CAS concepts, (2) profiling communities systematically over time to observe adaptive capacity as an ongoing dynamic, and (3) profiling the relative complexity of infrastructure, community, and organizational response of urban systems. The third item relates to autopoiesis (the self-producing capacity of CAS in terms of organization and information) and Ashby's Law of Requisite Variety (control systems must match the complexity of their environment), where autopoiesis is measured as the system's complexity divided by the complexity of its environment (Ashby, 1956; Gershenson, 2014; see Zhang et al (2006) for an example framed around information entropy of an urban ecosystem). A complexity approach to resilience metrics would be more focused on governance, interconnections, and capacities, but critical forms of capital are still an essential component as critical stocks for adaptive efforts. CAS and SES principles already provide a framework to conceptualize systemic resilience indicators for an evolving complex urban system, when indices are viewed as an on-going process. Further, these principles can drive a rethinking of quantitative assumptions used for index building, such as thresholds for indicators where the proximity to critical limits can transition an urban system or its subcomponents into resilience-hindering or undesirable states (Luers, 2005).

Two relevant areas of interdisciplinary research include adapting DRI frameworks with network-based methods, or with transdisciplinary methods that rely on multiple ways of knowing. Kammouh et al (2020) developed a resilience index for a transportation network using Dynamic Bayesian Network (DBN) techniques that enable time-dependent relationships between indicators. Bozza et al (2015) propose a Hybrid Physical-Social Network model (HPSN) that incorporates a vulnerability index within a built environment network at the neighborhood level that includes buildings and roads exposed to a natural disaster. Modeling cities at different scales with such methods can illustrate how resilience emerges when components of an urban system are made vulnerable at different levels of criticality. Complexity science for cities suggests urban systems have consistent systemic properties as they grow and are subjected to perturbations, so there may be opportunities to observe CAS tenets and resilience principles and develop metrics supported by computational methods (Batty, 2009; Bettencourt, 2013; Turner & Baker, 2019). Alternatively, coupling indices with ethnographic and other qualitative methods can illustrate how indicators and CAS concepts manifest in the experiences of community members, which can either confirm, deny, or add nuance to quantitative assumptions.

It is possible to experiment with indicators that more closely relate to CAS principles and systemic, process-oriented perspectives. Suarez et al (2019) propose an indicator set for assessing socio-ecological resilience in cities that overlap with many of the concepts of this paper, which can offer a fulcrum for research and development toward a CAS-oriented index. Geographically sophisticated approaches like multi-scale geographic regression (MGWR) assume that a set of indicators has place-dependent processes. Yoon et al (2016) used MGWR to develop a Climate Disaster Resilience Index (CDRI) and showed how established resilience indicators have different relationships in different parts of South Korea. Such methods relate to system histories and irreducibility in spatial terms. Places have a unique history, meanings, initial conditions, boundaries, and interconnections. Therefore, it is important for DRI to be amenable to continuous evaluation, revision, and adaptation to specific applications.

3.8.2 Toward Complexity-driven Development & Application of DRI

Co-production of DRI among research and practice, can support learning as a resilience principle, close the gap between top-down methods and on-the-ground realities (i.e., irreducibility of urban systems), and contextual adaptations of DRI (CITE). Community participation and engagement among and between communities, researchers, stakeholders, and decision makers is important toward ensuring that both the index methodology and the resulting resilience enhancing measures are not myopic, unrealistic, or likely to cause injustice and conflict. Participation can facilitate context adapted DRI by qualifying the applicability of generalized indicators, identifying essential drivers for resilience and specific slow (i.e., control) variables that reach critical limits for a given city's systems, and modify methodologies accordingly. In terms of the process of index development, Beccari (2016) and Asadzadeh (2017) discuss whether and how index methods incorporate participation for monitoring of results and adjustment of indicators, which can serve as a learning and experimentation process.

The need for adaptive methodologies is a cue for researchers and developers of indices toward algorithmic or modular methods that support participation, experimentation, and better align with an understanding of CAS. A simple example is an established SVI framework that was adapted with an alternative aggregation scheme and integrated into an interactive web-tool that decomposes indicators, made possible by collaboration with decisionmakers for the City of Knoxville, TN (Cutter et al., 2003; Flanagan et al., 2011; Nugent et al., 2017; Omitaomu & Carvalhaes, 2017). Van der Merwe et al (2019) developed and implemented a formative resilience assessment that leverages the seven SES resilience principles adopted here toward an on-going collective evaluation of resilience of an energy system. Formative assessments differ distinctly from top-down composite resilience indices (known as summative assessments), but such methods can be adapted along with composite methods for more holistic and robust outcomes, incorporation of participatory methods, system learning, and collective resilience thinking for communities and decision makers. Some emergent DRI approaches take on an understanding of CAS in terms of uncertainty regarding index outputs (e.g., DBN; Kammouh et al., 2019), and in terms of irreducibility and system framings (e.g., contextual exceptions, perceptual differences between stakeholders).

Recursive methods are also important because composite indices tend to be static when complex systems are in continuous evolution (i.e, urban systems are constantly changing). Such a process has two potential benefits in the effort toward robust metrics of disaster resilience. One, monitoring how variables change over time in respect to resilience outcomes can provide novel insights into key indicators for disaster resilience (i.e., longitudinal studies; Fekete, 2019). Different variables can emerge as critical between different disaster events due to slow variables that cause changes in urban systems over time, or changes in the nature of the event (e.g., hurricane intensity, frequency, or unprecedented events). Two, evaluating and re-evaluating the robustness and usefulness of indices post-application can address validation and contribute to index development. Applying DRI-driven resilience measures while investing in monitoring results can enable modification of methodological approaches as needed for different disasters or as resilience-related processes evolve, and contribute to urban resilience knowledge.

3.8.3 Broader Implications and the Future of Resilience Indices as a Form of Measurement

Resilience to disasters can range categorically from momentary failures to extended “Black Swan” events like COVID-19 (arguably a “black elephant”), and temporally from disruption to post-recovery periods (Asayama et al., 2020; Reddy, 2020). While resilience index approaches can range from specific hazards like urban flooding, many of the dominant frameworks take an all-hazards approach (at least climatic hazards in general; Cai et al., 2018). Literature differentiates between specified resilience, which incorporates foreseeable risks in terms of a specific challenge or normative aim (“of what, to what”) that can be managed by best practices and infrastructure design, and general resilience, pertaining to the overall ability for systems to adapt and transform upon all types of shocks, including unprecedented ones (Folke et al., 2010; van der Merwe et al., 2018). Trade-offs exist between investments for specified versus general resilience (Folke et al. 2010, Carpenter et al., 2012).

As COVID-19 emerged during the writing of this paper, variables that emerged as critical hardly align with previously established core indicators for DRI, such as safe and equitable digital access, the ability to isolate cases of infection, and multi-modal transportation (Amekudzi-Kennedy et al., 2020; Beaunoyer et al., 2020; Woods et al., 2020). Common indicators like emergency shelters and religious organizations promote specific resilience to disasters like hurricanes, but become problematic during disasters like pandemics. Established DRI methods may be more applicable when framed and developed in terms of a well-specified challenge. However, this should come with an understanding of potential trade-offs and limits in capturing elements of general resilience, such as the irreducible leadership and organizational elements that emerged as critical to COVID-19 (Allenby & Chester, 2020; Carvalhaes et al., 2020). Further research can clarify the validity and usefulness of proxies for systemic properties, such as the overall ability of an urban system to self-organize, toward indicating some type of general resilience.

From a broad complexity perspective, resilience indicators could aim to capture how resilience may emerge, rather than interpreting a place as having altogether "more resilience" than before, or relative to another place. Indices that can be decomposed interactively to pick apart indicators and indicator themes allow for this kind of observation, such as those that use GeoApp platforms where different levels of aggregations and layers of data can be dynamically viewed by planners and decisionmakers. Application-based indices become even more effective when applications support multiple layers of data that can qualify and add depth to indices like surveys and ethnographic descriptions (e.g., Kawano et al., 2016), or time series of index data. Creativity, reflexive use, and careful consideration of limitations and assumptions supports the effectiveness of DRI and enables them to evolve as complexity becomes a more prominent paradigm.

While there are arguments that the use of composite indicators and maps for resilience are insufficient, there is demand for such actionable and geographically oriented metrics (Eakin et al., 2018; see Butler, 1999 for an argument in context of sustainability indicators). The usefulness of these kinds of metrics comes down to not only how they are developed, but how they are understood and applied. DRI provide a momentary snapshot of how a continuously evolving urban system may cope and recover from a disaster. Even a CAS-oriented framework for DRI aims to reduce a system to its essential moving parts. Some reduction is necessary to make sense out of the system and take resilience-enhancing actions. While composite index methods may eventually prove to be too simplistic for complex systems, such methods can be used algorithmically to understand urban processes, or coupled in holistic frameworks with other types of analysis and transdisciplinary knowledge for a fuller picture of urban resilience. When the uncertainty of CAS is properly addressed, there is still value in having a litmus metric for resilience capacities and capital to make the case for resilience investments, build community and infrastructure capacities, and satisfy the demand for expedient tools to cope and prepare for coming disasters.

3.9 Conclusions

This paper outlined trends and connections among urban disaster resilience and complexity literature, and a common core of DRI indicators was identified and analyzed against CAS tenets and SES resilience principles. It is pointed out that resilience indicators could ultimately be categorized into two broad system dimensions: (i) essential forms of capital that act as stocks to support adaptation, and (ii) governance and community capacities that enable the flow of information and resources, and organization. Several review articles point to the necessity and difficulty of incorporating interactions between subcomponents and subsystems into index methods (i.e., system-of-systems).

An analysis of commonly adopted resilience concepts and indicators in terms of CAS tenets and resilience principles found that indicators only sometimes relate to systemic variables or proxy for the capacity of an urban system to reorganize after a disaster. DRI may be categorically misaligned with CAS by quantifying attributes of subsystems at one point in time and space, concatenating them to rank overall resilience (e.g., summative aggregation), and attributing meaningfulness to the subsequent index in terms of the process of urban response and adaptive capacity amid disasters. This paper discussed alternative framings of concepts, indicators, and methods that can serve as better proxies to the emergence of resilience. DRI can be interpreted in terms of how indicators proxy the ways resilience may emerge, rather than a rank order between places and snapshots in time. Resilience as “anti-vulnerability” has been further distinguished from resilience as an adaptive process in a complex system.Further work toward resilience index research and development should include validation (either statistical or cross-validation via stakeholder engagement, mixed-methods, or short case studies), and coupling interdisciplinary methodologies. Methods like thick mapping and spatial ethnographies combine quantitative and qualitative data, and show potential avenues for furthering innovative approaches for resilience assessment. Along with network-based computational approaches, these research foci can enable researchers to understand nuances regarding indicators, observe exceptions and limitations to indices, and enable novel tools for practitioners to determine how to harness adaptive capacities in the face of future disasters.

CHAPTER 4

INTEGRATING SPATIAL AND ETHNOGRAPHIC METHODS FOR RESILIENCE RESEARCH: A THICK MAPPING APPROACH FOR HURRICANE MARIA IN PUERTO RICO

4.1 Introduction & Research Questions

Positioned in the Caribbean Atlantic, PR is geographically exposed to relatively frequent and severe tropical storms that can cause damage to critical infrastructure systems (Diaz et al., 2018; Evans et al., 2011). While natural hazards like hurricanes are recurring events in the Caribbean, Hurricane Maria was unlike any other hurricane for Puerto Rico (PR), inducing unprecedented and prolonged impacts on critical infrastructure and the lives of the communities that rely on them (Pullen 2018; Zorilla, 2018). As the climate continues to change, it is expected that the frequency of the most intense storms will increase in the North Atlantic region where PR is situated (Stephenson and Jones, 2017). Meanwhile, Caribbean islands like PR are susceptible to extreme weather due to climatic interdependencies for the sustainability of economic and social ways of life, such as tourism and agriculture (Sheller, 2020; Taylor et al., 2012). Since Maria, efforts to enhance resilience have become an integral part of recovery and future visioning for PR (e.g., DOE, 2018; IRP, 2019; Ortiz, 2019). Plans to transition the electrical system toward more resilient configurations and fortify critical infrastructure remain in development, along with community and institutional level efforts to prepare and adapt to future challenges. However, it is unclear how well quantitative and technocentric perspectives (e.g., optimizing the electrical network with novel technological approaches) are modulated with institutional and social dynamics, or how individual and community experiences can be integrated as knowledge toward resilience and sustainable solutions.

Allenby and Sarewitz (2011) described technology as having three levels of complexity (systemic, system of systems, and transformative systems) and how technocentric solutions fail due to a near-sighted perception of technology that ignores sociocultural interrelationships. While technological solutions abound after disasters, resilience involves complex systems with intertwined cultural and physical phenomena (i.e., social, ecological, and technical dimensions). Complex systems cannot be reduced to a set of essential components that can be observed and modeled in a predictive way and are better understood in terms of relational information concerning many interacting, autonomous parts (Heylighen et al., 2006). For example, at the first level (i.e., systemic complexity), technology such as an airplane is constructed of the parts that make up the airplane so that the machine can fly. The airplane, as a system of mechanical parts, acts in knowable ways and with relative predictability. At the second level (i.e., system of systems), considering that an airplane requires a network of airports, personnel, and transportation infrastructure. Thus, level I technology is embedded in level II, a complex socio-technical system of air transport. This network is embedded in a third level (transformative systems) that accounts for extended sociocultural dynamics, where radical contingency and wicked complexity are at play. For instance, air travel accelerates the global effects of greenhouse gases, the rapid global spread of pandemics like COVID-19, and even cultural and geopolitical dynamics. At this level of technology, we must heed to uncertainty, the lack of universally valid goals, and the validity of any single perspective. This level of complexity is difficult for academic research because disciplinary structures and frameworks are undermined by context and meanings that are constantly shifting (or never fixed at the onset). Considering PR after Maria, it is vital to go beyond technocentric assessments to explore interconnected sociocultural dimensions that can impact resilience efforts.

The work described in this paper stems from a multi-pronged project supported by the National Science Foundation titled - Enhancing Resilience in Islanded Communities (Eric21.org) - with the objective, in part, of developing a data-driven socio-technical framework that can assess physical and social interconnections toward enhancing resilience in islanded communities. While any framing of a complex system is necessarily limited and partial (Cilliers, 2002), this paper attempts to capture multiple framings attached to a "space" (i.e., a bounded geographic region) and "place" (i.e., layered meanings and values related to a space) toward illuminating how resilience has emerged in PR and exploring respective socio-technical interconnections. While uncertainty and unpredictability are inherent in a complex adaptive system, multiple perspectives are necessary toward forming "complete enough" conceptualizations of systems and holistic solutions to adaptively manage future disasters (Allenby, 2012; Cilliers et al., 2013). This work describes a method for understanding disaster resilience and a platform for which future interdisciplinary outputs (including technical modeling approaches) can be integrated (e.g., hydrological modeling, power network simulations, and spatial ethnographies of subsequent events like earthquakes and pandemics). In this way, we aim to explore thick mapping as a methodology for disaster resilience and illustrate how otherwise disparate approaches can be moored to a common analytical platform.

Quantitative analysis such as engineering and geoscience approaches typically focus on highlighting priority areas, finding optimal solutions, and probable vulnerability. However, less attention is typically paid to the slow variables, outliers, and weak signals (especially in the sociopolitical and qualitative dimensions, such as trust, emerging social conflicts, or contested futures that undermine technocentric solutions) that may have consequences in the emergence of resilience or lack thereof (Allenby & Chester, 2018; Carpenter et al., 2001; Eakin et al., 2017; Miller et al., 2018). Alternatively, one way to understand a complex system is by creating detailed portraits of the system to gain insights from a particular vantage point (i.e., "a snapshot") or by creating a series of snapshots over time and space. Dynamic geographic mapping, such as web-based geospatial applications known as *GeoApps* (e.g., McCord et al., 2018), can enable such portraits from multiple vantage points and support interactive integrations of different kinds of information, such as scientifically derived metrics and participant interviews (Kawano et al., 2016). We propose further research that explicitly utilizes the idea of space to leverage ethnography and quantitative geospatial methods (e.g., mappable socioeconomic and physical metrics) in-tandem for resilience projects. In tackling the problem of handling socio-technological complexity and the multitudinous frames of reference that a complex adaptive system (CAS) such as Puerto Rico may have, the following questions guide the research presented here:

1. What forms of social capital and adaptive capacity emerged during and after Maria in PR?

2. How do quantifiable and physical variables (e.g., infrastructure performance, topography, location of community resources) manifest in community experiences across the island before, during, and after Maria?
3. How can quantitative and qualitative approaches be spatially integrated to understand resilience as a complex adaptive phenomenon?

We first situate the anthropological concepts of space and place (Coleman & Collins, 2006; Tuan, 1977) within resilience theory, adaptive capacity, and social capital frameworks (section 4.2). In section 4.3, we expand on the methodology, which integrates a method of distributed ethnography – web-administered ethnographies that capture geo-tagged personal anecdotes of the disaster - (supported by the SenseMaker® tool) with GIS mapping features to create a thick map of Puerto Rico (Tummons et al., 2015). Thick mapping is a set of concepts and methods developed within the digital humanities (described in greater detail in the following section) to create representations of place and incorporates the multiplicity of subjective records of a place (Presner et al., 2014). The process of this mapping is treated as a navigable interdisciplinary arena and is spatially and temporally situated. We thicken the map by incorporating layers that include geo-social and event-driven elements (Maria). We highlight results in section 4, then discuss implications for resilience in PR and how thick mapping can be leveraged toward integrated and interdisciplinary frameworks (section 4.5-6).

4.2 Literature Review: Space and Place for Disaster Resilience

Space and place are distinct and fundamental anthropological concepts for ethnography. Space is often defined by an abstract scientific, mathematical, or measurable conception, while place refers to the elaborated cultural meanings people invest in or attach to a specific site or locale (Lawrence-Zuniga, 2017). In other words, space speaks to the physical and sensory phenomena of a location, whereas place refers to the many layers of contested experiences and narratives connected to a space. Places are invariably parts of spaces, and spaces provide the resources and the frames of reference in which multiple places are made (Agnew & Livingstone, 2011). Influencing factors of “place” do not lend themselves as well to spatial mapping and tend to require qualitative data, so it is important to be as attentive to space and nature as to human creativity and cultural production for ethnographic approaches to resilience (e.g., Chari & Gidwani, 2005). Space lends itself well to abstraction of static maps (i.e., pertaining to “object” worlds where situations are constant and tangible, such as with topography), but “place” transcends “thingness” and is critical when seeking to make sense of the complexities of sociocultural and politico-economic life that contributes to the making of a place.

`Since it is crucial to be as attentive to space and nature as to human creativity and cultural production for ethnographic approaches to resilience (e.g., Chari & Gidwani, 2005), there is room for alternative approaches to geospatial mapping that can better capture complexity and influencing factors of place. Since complex systems are in constant flux (i.e., ongoing adaptation and evolution through space and time), resilience can arise from governance and designed interventions that embed ongoing interaction (mapping, sensing, and hacking the system; Chandler, 2014; 2018), and the range of disaster responses based on the effectiveness of individual and collective sensemaking (Doyle et al., 2015; Nofi, 2000, Van der Merwe et al., 2018). Karl Weick (2001) likened sensemaking to cartography. Mapping becomes a part of the process for ongoing sensemaking, where sensemaking is the process of developing a shared understanding of the situational dynamics, perspectives, and changes under uncertainty (Kurtz & Snowden, 2003). When working in uncertain environments or with known unknowns and unknown unknowns, we recognize that a map's utility is not a depiction of accuracy, but part of the sensemaking process through which we understand space and place.

Through analysis of individual and community narratives, ethnographic methods can uncover capacities for disaster resilience inherent in a space and place. Such methods can be used to map more elusive aspects of resilience like social capital (the many types of social networks and cohesion that realizes resources amid disasters; Aldrich & Meyer, 2015), adaptive capacity (the ability for individuals, communities, and infrastructure to adapt to disruptions; Engle, 2011), and governance (all of the processes that govern an individual, resources, or territory including social networks and informal institutions; Bevir, 2012). Aldrich (2012, 2017) suggests that social capital is a critical contributor to community resilience and is linked deeply to community linking value to the "place" of their community belonging. Social cohesion keeps people from leaving disaster-struck regions, allows for the easy mobilization of groups, and provides informal insurance when regular resource providers are not open.

Conversely, established approaches such as vulnerability and resilience mapping are sometimes criticized for lacking dynamism and not capturing complexity, but they do offer measurable indicators that can be visualized from a non-local aggregate (i.e., larger scale) perspective (Asadzadeh et al., 2017; Cutter, 2016a; Eakin et al., 2017). Geographical aspects (both human and physical) of the landscape such as climate, infrastructure networks, and demographic distributions are still at play through the resilience process, and manifest technically (e.g., physical vulnerability to floods) and subjectively (e.g., risk perception, social connectivity). In this way, resilience can be observed from both non-local (i.e., aggregate, quantitative level) and local (e.g., ethnographic interviews, participant observation) perspectives.

Subsequently, there is a challenge regarding how qualitative in-depth data and analysis of resilience capacities interface with technical analysis of the natural, human, and built environment. While qualitative methods dominate disaster resilience research, relatively few studies have applied mixed methods approaches that map multiple perspectives of disaster resilience at different scales (Witt and Lill, 2018). A thick map, which incorporates the ability to account for the dynamic interplay between scale and layers, can potentially capture how spatial attributes of the natural and built environment influence personal and community experiences of disaster and recovery and vice versa. That is, how individuals and communities collectively make sense of their realities during the process of a disaster event.

4.3 Methodology

This paper presents a thick mapping approach that blends basic geo-visualization with scaled ethnographic and quantitative geospatial analysis (Fig. 4.1). The approach focuses on representing the complexity inherent in disaster recovery and the systemic cultivation of resilience. The map is informed by the contexts and implications of PR as a space and place, and leverages the relatively recent concept of thick mapping (Presner, 2014). Thick mapping embodies temporal and historical dynamics via place-specific and geographic data in a multiplicity of layered (and contested) narratives. In the digital age, maps are now readily dynamic, networked, and mobile, rather than static and artifactual, as in traditional cartographic approaches. Digital dynamism allows GeoApps to become analytical tools and interactive outputs that can be embedded into the sensemaking process of research.

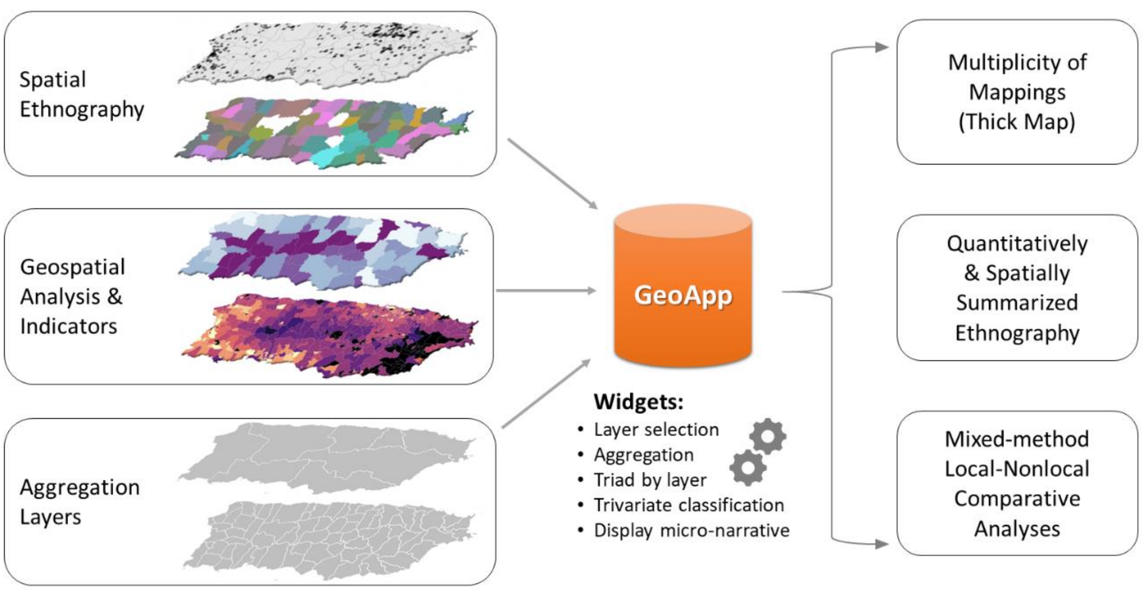

Figure 4.1. Overview of methodology for integrating different research approaches into a thick digital mapping of resilience to Hurricane Maria in PR.

Notable studies have leveraged thick mapping-oriented concepts and methods for resilience research. Gotham and Campanella (2013) conducted a spatial ethnographic exercise to study how resilience manifested in New Orleans after Hurricane Katrina. Using census data and GIS, they were able to quantify flood risk and map this to social diversity and repopulation rates over neighborhoods over time. They coupled this with ethnographic interviews with various stakeholders and community members. Their study revealed how quantitative spatial analysis manifested in the daily lives of residents. For instance, it was found that attachment to place, a commonly adopted indicator for community resilience, emerged as a strong indicator of neighborhood resilience in the study. However, their ethnographic results revealed that place attachment takes on different meanings for residents and is not a static indicator; it had to be dynamically reinforced through place attachment generating activities such as improvement of the physical regeneration (enhancing walkability, reducing environmental degradation) and connection with the social memory and collective meaning-making around the neighborhood. In this way, they triangulated methods and data sources to enhance validity, reliability, and insight. Where mixed analyses converge, we can have greater confidence in the results (e.g., place attachment is a significant variable for resilience), and where they diverge, we may find nuances and contextual effects (e.g., the forms and meanings of place attachment vary greatly from place to place).

Community resilience indicators are also influenced by context. Illustrating this, Rickless et al. (2020) uncovered the significant differences in vulnerability perceptions across ethno-racial and income divides, which influence place attachment as an indicator. These nuances were uncovered through a mixed-method geo-visual approach integrated with a census-based social vulnerability index and a human subject-based survey. Researching social vulnerability after the impacts of Hurricanes Matthew and Irma to the Georgia Coast, the study found that survey-based findings tended to align less with quantitative composite indices (i.e., Social Vulnerability Index) in densely populated areas, likely because of greater demographic heterogeneity. Kawano et al. (2016) augmented a spatial ethnography with scientific data to study post-tsunami resilience in Fukushima, Japan. Using a combination of geovideography (geospatially enabled audiovisual techniques and content), scientific analysis of radiation levels, and ethnographic interviews, the project mapped post-disaster experiences in terms of spatial-temporal narratives that incorporate both objective and subjective variables. A dynamic web map was produced to analyze data and distribute findings to stakeholders.

The study presented here builds on these thick mapping approaches. A combination of three methods are used to develop a GeoApp that dynamically and spatially represents the community experiences of Maria through (i) distributed ethnography through the collection, coding, and analysis of community narratives; (ii) geospatial analysis of electricity recovery through night lights data, and integrated resilience and vulnerability indices based on publicly available data; and (iii) interactive geo-visualization of the natural and built environment (e.g., topography and urban density). The three methods are described as separate elements in the following sections but are ultimately integrated into the interactive GeoApp[10].

[10] GeoApp available at https://varinaldi.shinyapps.io/triadGeo/

4.3.1 Method I: Spatial Ethnography

One way to understand the complexities and subjectivities of a place is to gather a range of personal and community narratives to be analyzed iteratively for key themes, slow variables, and contested ideas. For example, Borie and colleagues (2019) mapped narratives regarding the role of science in urban resilience from a Science and Technology Studies (STS) and critical social science perspective. In this paper, we utilized the SenseMaker tool to augment the ethnographic study of the Maria experience in PR. The tool allows us to collect narratives as short anecdotes and visualize these hard-to-map aspects such as social capital and community resilience. The tool features a signification system that allows participants to code their own stories at the point of capture via signifiers (established concepts to relate and anchor the plotting of narratives in space explicitly), collecting both qualitative experiential data and quantitative meta-data in an integrated way (van der Merwe et al., 2019). Established literature was leveraged to design signifiers that capture resilience capacities (Table 4.1), such as the ability for communities to link to institutions, other communities, or bond with community members to leverage social capital during times of crisis (Aldrich 2010, 2012).

The tool was administered by a web-mounted site (available in English and Spanish). Each respondent begins by sharing a story about their experience with Maria, then assigns pre-designed signifiers to indicate the balance of influencing factors as experienced in their narrative. While it was intentional to capture narratives in urban and rural areas, data gathering relied mainly on the snowball method applied by local students toward their communities and friends (Ghaljaie et al., 2017). Allowing respondents to code their narratives alleviates researcher bias common in other ethnographic approaches, such as systematic errors that romanticize reported results (van der Merwe et al., 2019; Rohner et al., 1973).

Table 4.1. Designed signifiers for resilience, vulnerability, and adaptive capacity. Signifiers presented as triads (relative ranking between three elements) are denoted with the prefix "T" in the first column. Signifiers presented as dyads (a slider between two elements) are denoted with the prefix "D".

Signifier	Description
T1. Perceived impact	***Property - Human life - Infrastructure*** Assesses type of general impact described in specific experiences and perceptions of how each type of impact relates to another.
T2 Resilience capacities	***Absorptive*** - Persistence; buffering capacity to absorb short-term disturbances or within thresholds. This is useful during the beginning phase of shocks. ***Adaptive*** - Incremental adjustment; system's ability to adjust itself to maintain functions. Capacity might reveal itself through resourcefulness, learning through failure, and ability to mobilize resources. ***Transformative*** - Transformational responses; might involve institutional reform, behavioral changes, and technological innovation. (Bene et al., 2012; Cutter et al., 2008; Pelling, 2010)
T3 Social Capital	***Bonding*** - Connects kin and friends. Concept of homophily, reinforcing existing relationships and bonds with people of similar backgrounds. ***Linking*** - Providing access to power brokers, or groups, traditionally unfamiliar or out of reach. Puts communities "on the map." ***Bridging*** - Works through institutions, connecting different groups of people. Institutions act as a conduit to dampen intergroup differences and level out unequal access to resources and opportunities. (Aldrich, 2012; 2017)
T4 Improvements	***Tools - Communication - Cooperation*** Follow-up, operationally focused question to understand where focus can be placed on building more capacities for resilience and where efforts can potentially create the most impact.
T5 Critical infrastructure	***Water - Electricity - Communication and access*** Identifies critically resilient infrastructure, dependencies, and interdependencies as people experience them.

D1 Community culture	Seek to understand the role of participation, identity, and belonging in a community. ***Atomistic*** - Atomistic communities display high levels of individualism, which could be suitable for innovation and experimentation, but lacks resilience and scale. ***Communitarian*** - Highly communitarian groups display more uniformity and might have a stronger sense of belonging and mutual care. However, they tend to display less creative adaptability and ability for innovation and transformation.
D2 Innovation culture	Seek to understand where adaptive capacities were developed and found from the experiences. ***Tradition*** - Relying on traditional means - e.g., gathering wild food sources (i.e. bread food) that rely on traditional knowledge—an absorptive or adaptive capacity. ***Innovation*** - Relying on innovation and exaptation (creative repurposing) to develop coping mechanisms. Transformative or adaptive capacity.

With respondent tagging, we create a layer of high abstraction meta-data that enables quantitative and spatial analysis of large volumes of ethnographic data without the need for additional researcher intervention. Quantitative plotting of the narratives is done by trivariate indexing of signifiers, or “triads” (Fig. 4.2), and bivariate indexing of signifiers along a slider scale from 0-100, or “dyads” (Fig. 4.3). Respondents are requested to share demographic information to interpret responses further and enable cross-group analysis (e.g., age, gender). Additionally, narratives are geo-tagged (label with geographic coordinates). In turn, spatial mapping provides a framework to integrate ethnographic data with objective contexts, allowing us to corroborate across different data sources (e.g., night lights and electricity distribution across the island).

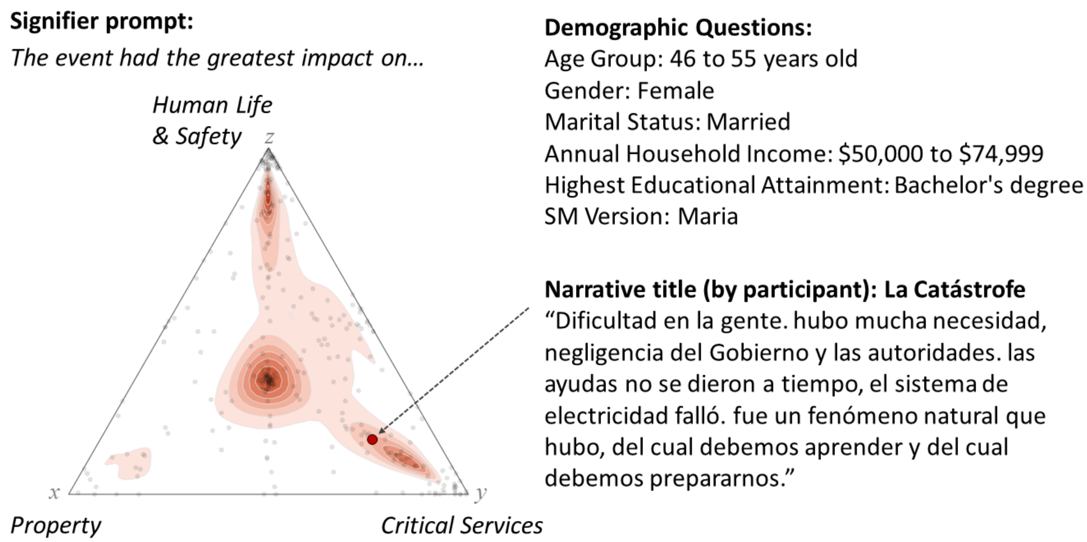

Figure 4.2. Example narrative and respective triad as a heatmap. Grey dots are individual data points corresponding to a prompt with signifiers in each of the triangle's three corners (human life and safety, property, critical services). The narrative text shown in the lower right is coded by the respondent, who places a point inside the triad indicating the balance between each of the signifiers (the red point). The point results in a coordinate (x, y, z) that can be quantitatively analyzed and grouped in different ways, including socioeconomic status and demographic data (shown in Figure 4.2, top right).

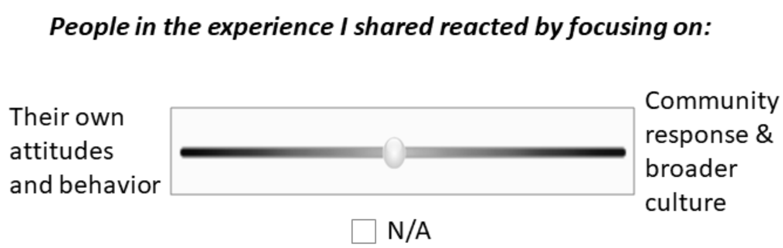

Figure 4.3. Example of a dyad prompt where respondents may signify how their experience as shared through the narrative relates to atomistic behavior (left-most side of the slider with a value of 0) and communitarian behavior (right-most extent of the slider with a maximum value of 100).

4.3.2 Method II: Geospatial Indicators & Analysis

Layering and Aggregation

Multiple levels and types of boundaries are possible to aggregate coded triads and other data for PR. A series of layers were included that capture aggregation levels, spatial ethnographic data, sociological data, and infrastructure data. For political boundaries, typical levels of analysis for social variables were carried out at county, sub-county, and state levels. Municipalities are the county equivalents for PR. Therefore, municipalities were included as one of the geographic boundaries to summarize coded triad data based on the size and spatial relationship to other variables. There are 78 municipalities in PR (Fig. 4.4), two of which are small islands off the coast.

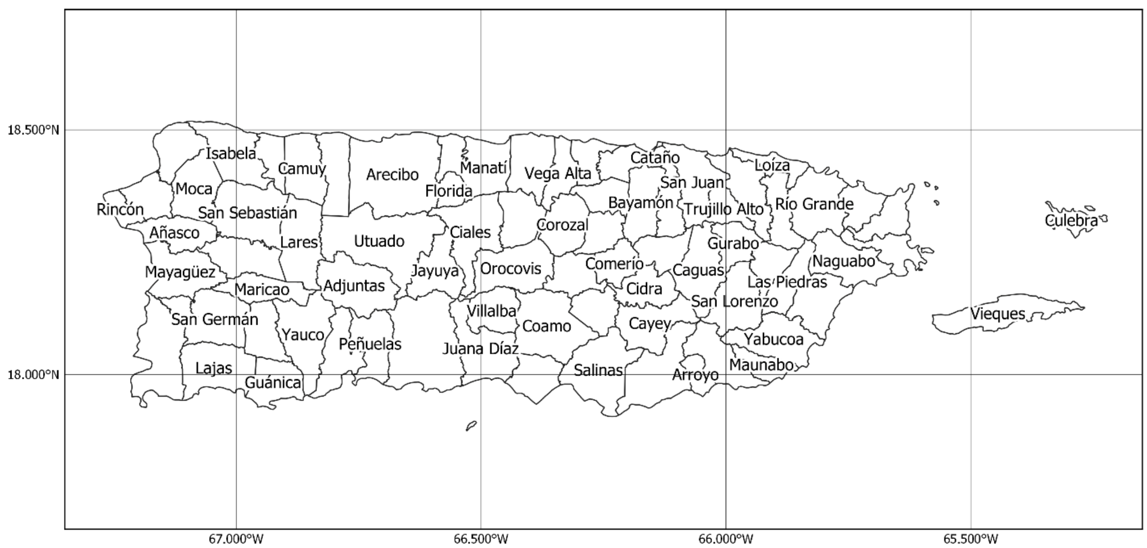

Figure 4.4. Municipalities of PR with geographic coordinates shown in the *y-axis* (latitude) and the *x-axis* (longitude) (Census TIGER/LINE 2017).

PR has mountainous regions, which include rural areas, nature preserves, and agricultural land uses. Figures 4.5a and 4.5b show the island’s topography and population density. Aside from typically having lower population densities, these mountainous regions have been shown to have different ecological and orthographic effects upon tropical storms and hurricanes. Therefore, both municipality averages and three isoclines were chosen to aggregate elevation values within the application to observe data patterns based on physical geography characteristics of the island. Lastly, since this study is primarily focused on electrical power networks in terms of infrastructure, PREPA (Puerto Rico Power Authority) management regions were included as aggregation boundaries within the application. There are currently 8 such regions within the island (Fig. 4.5c). Boundary layers such as these (i.e., municipalities, regions) spatially aggregate the geo-tagged and quantitatively plotted narrative data (e.g., by the geometric mean of a specific triad in respect to each bounding municipality). Characterizing each boundary in respect to triads and dyads can help profile clustering patterns, potential local trends, and variance in terms of responses to disasters, and tie a set of detailed information regarding an event and a place (i.e., individual stories of H-Maria, resilience indicators), which enables a series of integrated and comparative studies.

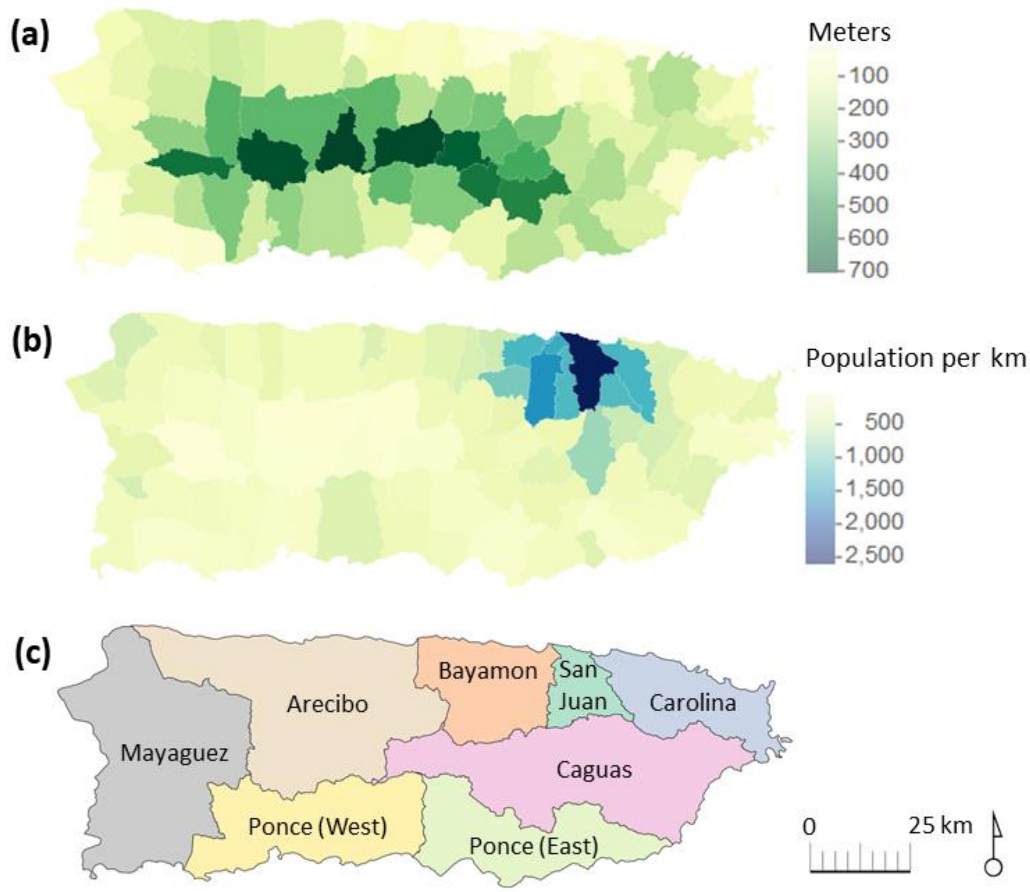

Figure 4.5a-c. Selected geographic attributes of PR relevant to the thick mapping analysis. The first map at the top **(a)** shows the topography visualized as elevation values aggregated at the municipality level within GeoApp. The middle map **(b)** shows population density aggregated by municipality viewed within GeoApp (Census ACS, 2017). The lower map **(c)** shows labeled PREPA planning and management regions during the Maria hurricane event (Source: https://aeepr.com/es-pr/Documents/Mapa%20Regiones.pdf).

Nightlights-based recovery index

Spaceborne detected Nighttime Lights (NTL) imagery from the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor is a reliable source to estimate power loss and recovery in PR due to Maria (Román et al. 2019). The Satellite sensor can capture the light radiance emitting from the ground at 500-m resolution (Fig. 4.6a-b). To reduce noise, imagery data was aggregated by month for a more robust estimation of power restoration. Power infrastructure capacity was considered as 100% before Maria, after which capacity suddenly drops and ultimately begins to recover. The available power capacity for a month (X) can be formalized with the following equation,

$$AvailablePowerCapacity = \frac{NTLradiance \in August2017 - NTLradiance \in (X)}{NTLradiance \in August2017} \times 100$$

Here, the NTL radiance before Maria (August 2017) was considered a baseline to estimate available power for a given month after Maria in percentage (compared to shortly before the Hurricane). Later, the number of months after the Hurricane needed to reach 70% of the NTL capacity was calculated to estimate the recovery speed for each census tract.

(a)

(b)

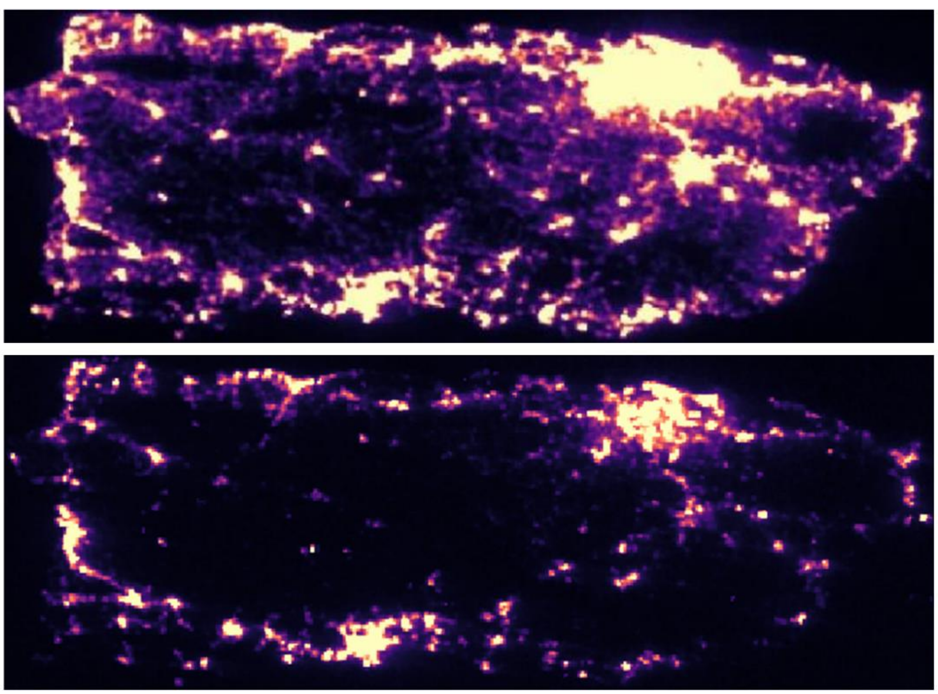

Figure 4.6a-b: Nighttime lights one week before (a) and one week after (b) Hurricane Maria

Resilience Indicators

Methods for developing community resilience indicators are well established in community psychology and disaster resilience literature (Berkes & Ross, 2013; Cutter, 2016a; Rus et al., 2018). Some of the most widely adopted methods rely on publicly available demographic and sociological data that can be used to rank relative resilience based on spatial boundaries, such as Cutter et al.'s (2010) Baseline Resilience Index (Beccari, 2016). However, several standard variables normally available for mainland states are unavailable for PR; given it is an unincorporated territory, the island does not always participate or is not included in national data programs. Thus, some commonly used vulnerability and resilience index systems are available for PR, while others are not (e.g., Baseline Resilience Index for Communities or BRIC).

The Social Vulnerability Index (SoVI) was publicly available and incorporated into the GeoApp tool. However, more comprehensive and resilience-oriented indices have since been developed for other areas. The SoVI does not include certain variables that relate to the scope of the narrative capture, signifiers, and resilience theory, such as those that indicate place attachment and social capital. Therefore, a PR-specific version of the BRIC was developed by adapting available data and following established methods (Cutter et al., 2010; Flanagan et al., 2011) to incorporate resilience themes (e.g., community capital) (*see supplementary material for details*).

4.3.3 Method III: Interactive Geovisualization

The data described in the above methods were integrated into an online mapping tool used dynamically to analyze the patterns that emerge with different aggregations and combinations of data layers (i.e., GeoApp)[11]. Over the process of data gathering, analysis, and application development, an iterative and reflexive process that leverages concepts that can interface between disciplinary approaches (e.g., space, linking local to non-local observations) was exercised to enable emergent research outcomes toward both the method development and research results (Fig. 4.7). This process was meant as an exploration that allows abductive reasoning in tandem with more traditional theoretical perspectives. Working toward a framework that synthesizes multiple disciplinary perspectives remains a common research goal that guides the broader effort. The development of the GeoApp is a tool-based manifestation of the research goal and facilitates the cross-domain and multi-level exploration of data, formats, and analysis.

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[11] GeoApp code available on Github repository: https://github.com/varinaldi/ThickMapMaria

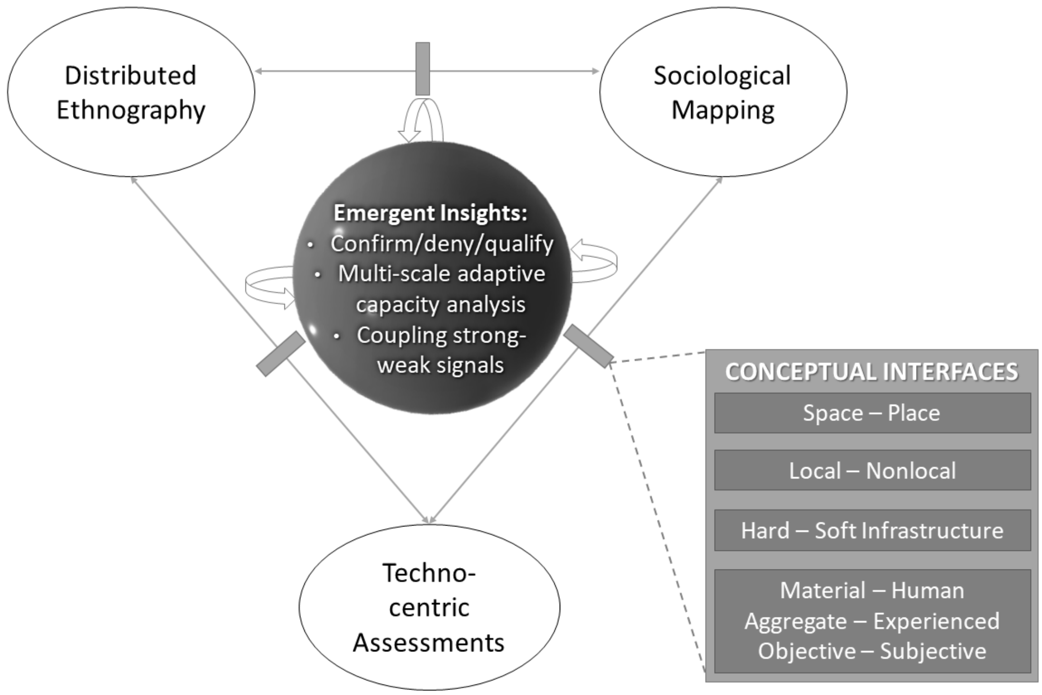

Figure 4.7. Conceptual framework for integration of geospatial and ethnographic approaches. Key concepts are used as boundary objects that interface between disciplinary approaches and data types.

4.4 Results & Summary

Three hundred sixty-five (365) stories were collected, participant-coded for each set of signifiers (i.e., dyads and triads), and geocoded in 67 of the 78 municipalities in PR. Samples were collected across the island, though higher densities of data points were observed in urban areas such as San Juan and Ponce, which is likely due to the capture method largely relying on social networking between participants (Fig. 4.8). Table 4.2 summarizes results in terms of each signifier (dyads and triads), which are then discussed in the integrated results that follow.

Figure 4.8. Distribution of data points for spatial ethnography.

This section will provide a synthesis of results regarding the spatial ethnography and geospatial analysis by focusing on a demonstrative set of triads and dyads that represent key themes and findings for socio-technical resilience. Approaching the results in this way honors the intent of integrated methods toward a socio-technical resilience assessment. The results from the integrated methodology can be broadly characterized as two emergent themes: (1) Social capital and community responses, and (2) the role of hard and soft infrastructure in socio-technical resilience (for complete and detailed results, see https://varinaldi.shinyapps.io/triadGeo/).

Table 4.2. Summary of distributed ethnography results by signifier (see also Table 4.1).

Signifier Triads (T) & Dyads (D)	**Results Summary**
T1. Perceived general impact	Respondent concerns tend to increase for critical infrastructure services and decrease for property as recovery proceeds.
T2 Resilience capacities	Responses trended toward adaptation and transformation over persistence, highlighting the ability to make changes and find new ways to support necessary community functions as a key capacity.
T3 Social Capital	Social capital emerged primarily in the form of reinforcing trusted relationships with friends and neighbors (bonding) and connecting with others (bridging).
T4 Improvements	Respondents highlighted the need for better tools, equipment, and technology, such as improved road access or medical equipment. Information on what to do was also a significant outcome, suggesting that awareness and preparedness efforts may be impactful along with the deployment of technical capacities.
T5 Critical infrastructure	Results point to hardships due to long recovery times for power and communications services and the overall importance of communications and access to recovery.
D1 Community culture:	Community culture trended toward collective attitudes rather than individualized responses.
D2 Innovation culture:	Narratives trended toward creative repurposing and innovation as key adaptation strategies. Respondents recognized Maria as an unprecedented event, suggesting new ways of coping may have been necessary.

4.4.1 Social Capital and Community Responses

Although PR has long experienced periodic hurricanes, results show that Maria was "unlike any other hurricane in the past," if not unlike any other event in ones' life. Respective stories included indications of strength, unity, and even positive outlooks:

"It was at that moment of crisis that I discovered my value as a person and the importance of my emotional health. "I lost everything," I said, and with each step I took I listened to worse experiences, however I began to value my talents and my resources, I still had life, I had a family, I had health and I had dreams. Since then, I began to dream big not in material matters, but rather in the spiritual one and I used what I learned to find again the path that would lead me to fulfill my dreams no matter the circumstances you go through."

"I would tell the child with a lot of emotion and feeling as a united people rose from the ravages of a natural phenomenon not previously seen; Like everyone, regardless of the differences, they helped each other and fought for a better tomorrow."

Stories such as these indicate a growth mindset, a concept previously associated with enhancing resilience (Dweck, 2008; Yeager & Dweck, 2012). While some stories mentioned resilient attitudes, others highlighted the burden of uncertainty associated with the lack of communications:

"*The greatest sadness was that the help took a long time to arrive."*

That Maria was unlike any other event aligns with participant responses regarding how people responded to the disaster, which more often trended toward adaptation (making small changes as needed) and transformation (forming drastically different living conditions), as opposed to maintaining normal ways of living, or persistence (Fig.

4.9). These results suggest that the ability to absorb changes and carry on routinely was less prevalent (or useful). During such a major rupture like Maria, making changes and finding new ways to support necessary community functions emerged as more vital.

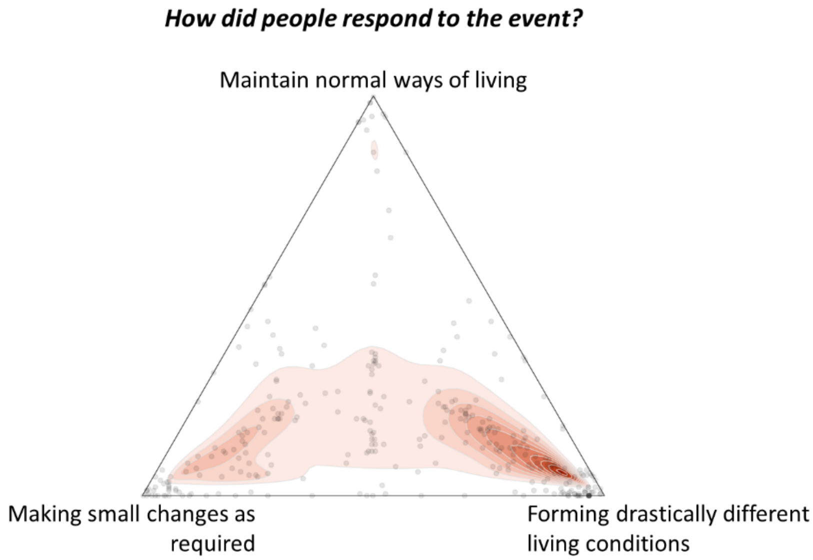

Figure 4.9. Resilience capacities triad represented as a heatmap. The three coordinates code for emphasis of the self-coded micro-narrative toward persistence, adaptation, and transformation.

While narratives tended to code more heavily toward transformative disaster responses, which generally rely on repurposing assets and creating new adaptive processes, they also tended to code experiences as more communitarian (collective attitudes and values) than atomistic (individual coping), which can sometimes suggest limited individual creativity and innovation (Fig. 4.10a-b). Results, however, show how community-level innovation can occur in-tandem with processes that enable community bonding and bridging when disasters demand entirely new ways of coping and established protocols are unviable (i.e., as observed through figures 4.11 and 4.12 in tandem, and discussed later in Theme 2).

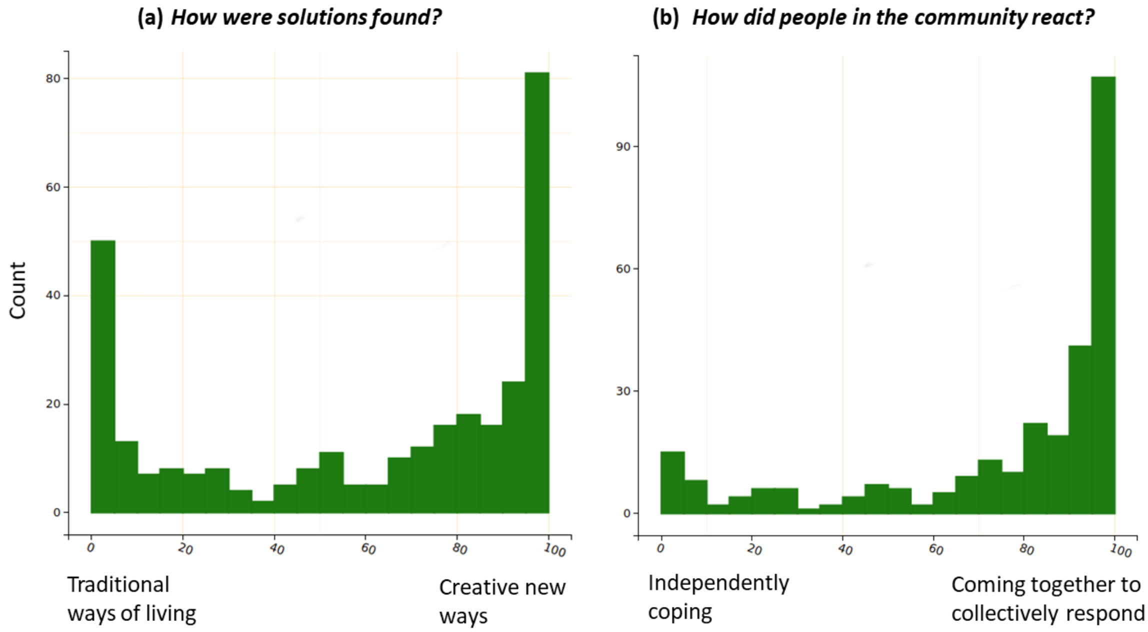

Figure 4.10a-b. Dyads coding for (a) the role of participation, identity, and belonging in a community where values closer to 0 relate more to atomistic behaviors and those closer to 100 relate to communitarian behaviors, and (b) how adaptive capacities were developed and found from the experiences where 0 relates to more traditional means and 100 to more transformative processes.

Further describing the shape of social capital in terms of community responses to Maria in PR, narratives trended heavily toward reinforcing trusted relationships with friends and neighbors (bonding) and connecting with others (bridging), rather than toward linking to organizations and institutions (linking) (Aldrich, 2017) (Fig. 4.11). Such results indicating the importance of community bonding and bridging, together with communitarian attitudes and transformative responses, show PR communities' capacity to cooperate while undertaking high degrees of change and experimentation.

This trend was especially evident in the mountainous regions, which become apparent when selecting triads by high-elevation topographies. In Adjuntas, Jayuya, and Orocovis, which are among the highest elevation municipalities, triads signifying social capital capacities were coded strongly toward reinforcing existing relationships, and secondly, connecting with others, rather than linking with organizations and institutions. Looking closer at the respective narratives, experiences highlighted the importance of local support and strength from having overcome previous experiences (Fig. 4.12). Mountainous areas in PR tend to be rural (or agricultural) and have been characterized by limited access (island within an island) for residents and repair efforts after Maria (Kwasinski et al., 2019). Ethnographic results reflect such qualities of this space and the tragedy of self-sufficiency that comes with a place that is frequently waiting for extended periods after disasters due to low prioritization, often based on population density and road access.

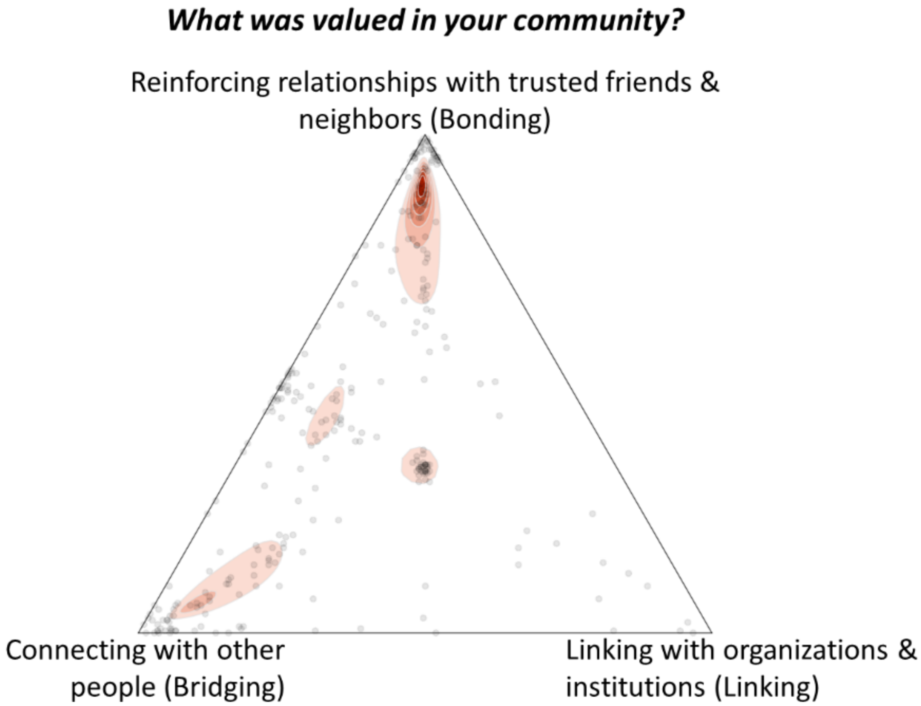

Figure 4.11. Emergent patterns for Social Capital triad. Bonding speaks to reinforcing trusted relationships with friends and neighbors., bridging to connecting with others, and linking to organizations and institutions.

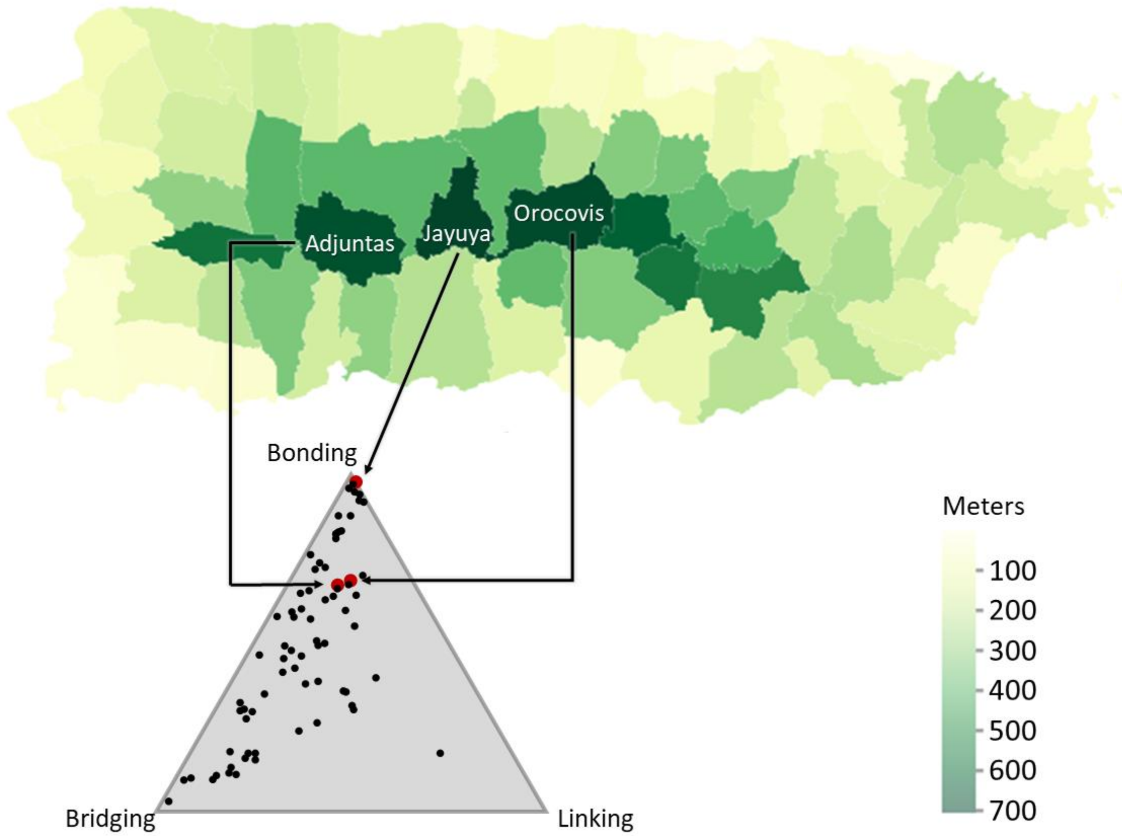

Figure 4.12. Relationship between elevation and ethnographic results for social capital signifiers of bonding (reinforcing relationships with trusted friends and neighbors), bridging (connecting with other people), and linking (linking with organizations and institutions). Each point in the triad corresponds to the geometric mean of the triad coordinates for each municipality. The three red coordinates highlight municipalities in mountainous regions: Adjuntas, Jayuya, and Orocovis.

However, some of the narratives suggest that the reason for the imbalance of social capital as away from institutions may be due to lack of trust, or at least lack of access or faith in the effectiveness of public institutions for providing help, as one respondent would tell a child:

"I would tell him about the uncertainty that was experienced in the government. It was at the point where there were supplies for the entire island, but the lack of communication, among other factors, made me a little scared. Since it could create a panic in society and communities."

"The government did little to help and much was stolen ... it is a shame."

4.4.2 The Role of Hard and Soft Infrastructure in Socio-technical Resilience

Considering critical infrastructure impact and recovery, island-wide patterns stress the importance of communications and access to recovery over electricity and water infrastructure (Fig. 4.13).

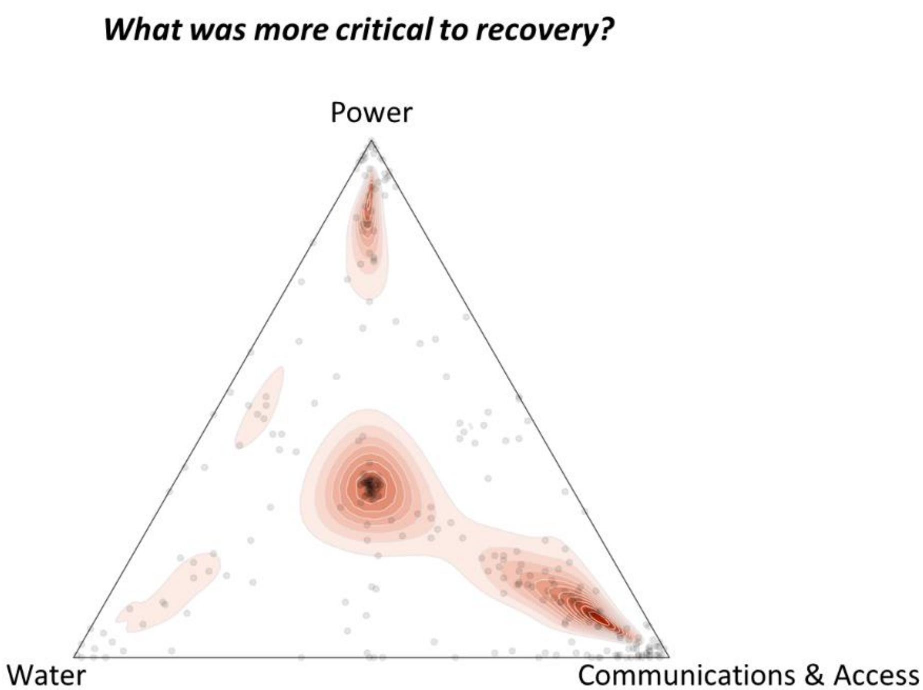

Figure 4.13. Emergent patterns for the Critical to Recovery triad.
Some narratives illustrate the ways that community capital and infrastructure adaptation can be used to cope with the lack of centralized infrastructure services:

"I saw a guy in the mountains that had a cistern, a washing machine, and a generator in the back of his pickup truck. He was driving around offering mobile laundry mat services. This is when there was still no power or water service."

These narratives highlight how local innovation, a growth mindset, and modular technological components can be leveraged locally for providing infrastructure services when centralized systems are down. Gas, HAM radio, rainwater collection, and access to ice are included in the kinds of locally accessible wares that can assist in coping without public infrastructure services and maintaining or recovering community services after Maria. However, some of these resources are interdependent with other systems that can involve complications. For instance, gasoline and diesel enable energy services through generators and access to other resources like food and medicine, but many stories highlighted difficulties in obtaining fuel when transportation systems and supply chains were disrupted (i.e., long lines, road access).

Grouping critical services triads in a temporal fashion displays patterns similar to the energy recovery index. Filtering by narratives related to longer-term recovery, the GeoApp highlights a greater emphasis in the Southeast region, where energy infrastructure recovery was relatively slow. When data points are grouped into narratives pertaining to before, during, immediately after, and longer-term after Maria, aggregated triads for municipalities trend toward a greater emphasis on critical infrastructure services while property becomes less of a concern as the duration after the event extends and the recovery process continues (Fig. 4.14). This is relatively intuitive since property damage is usually incurred while the storm is still carrying on. Furthermore, with the increasing duration of the loss of essential services like power, water, and communications, the criticality of such infrastructure manifests in the coded results of the narrative collection. Such results align with established literature that uses different types of analysis, such as survey and focus group-based methods, that find critical points where the duration of infrastructure service loss is related to a logistic increase in human burden (e.g., King, 2012). Power and communications were especially problematic due to a long recovery time.

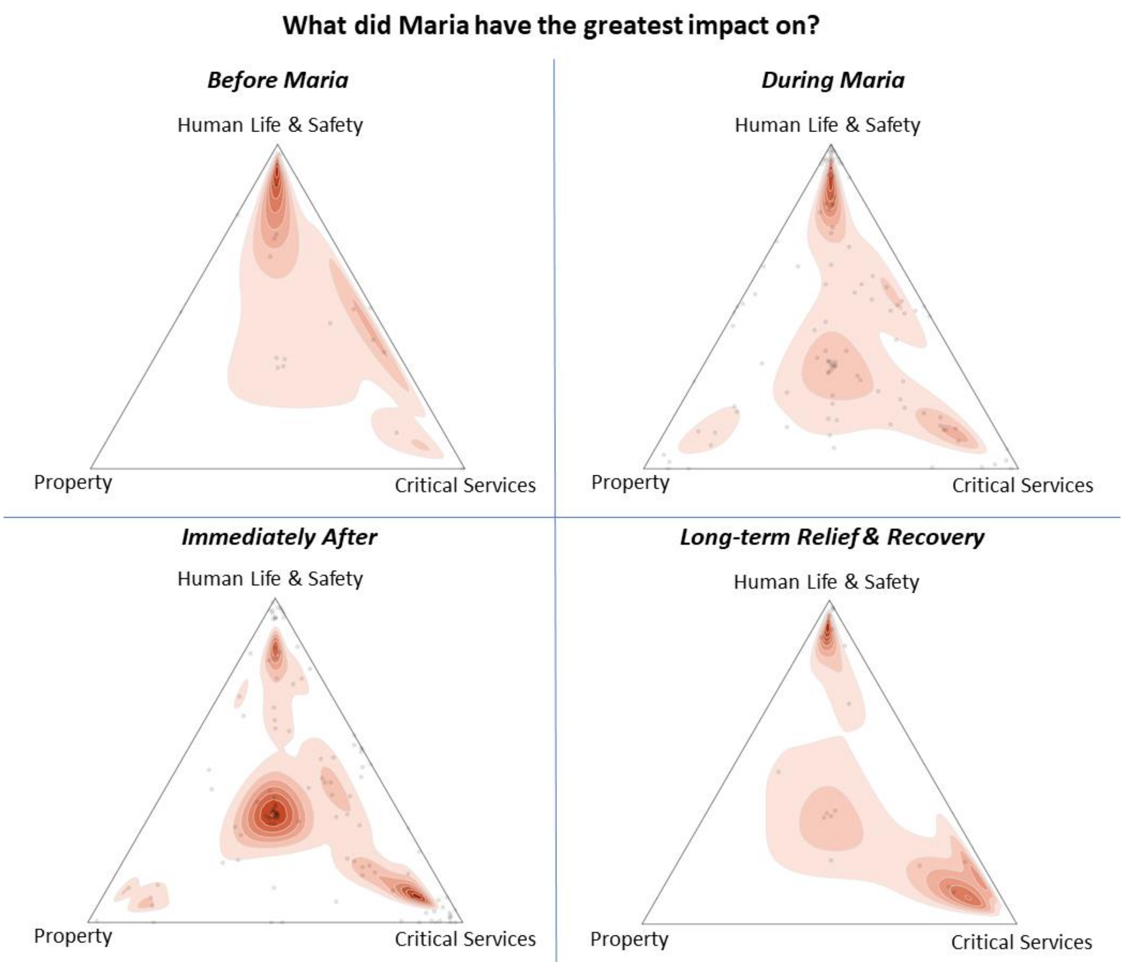

Figure 4.14. Patterns for the concerns between safety, property, and critical infrastructure services at different stages of H-Maria.

Lastly, triad results for improving resilience to future disasters display various clusters (Fig. 4.15), but most micro-narratives coded for better tools, equipment, and technology. The types of tools and technology varied among different stories, but many of them referred to hardships and adaptations necessary amid lack of power, access to roads, and medical equipment for the elderly and disabled. Additionally, some of the stories described the lack of communications (particularly to hear from loved ones) as inducing worry and uncertainty. Information on what to do also represented a large cluster, suggesting that technology alone may not generate more resilient outcomes, and preparedness efforts may be an impactful strategy. As is discussed later in this paper, access and trust for public institutions may be related to communications and processes for information that are key socio-technical dynamics that can impact technological improvements.

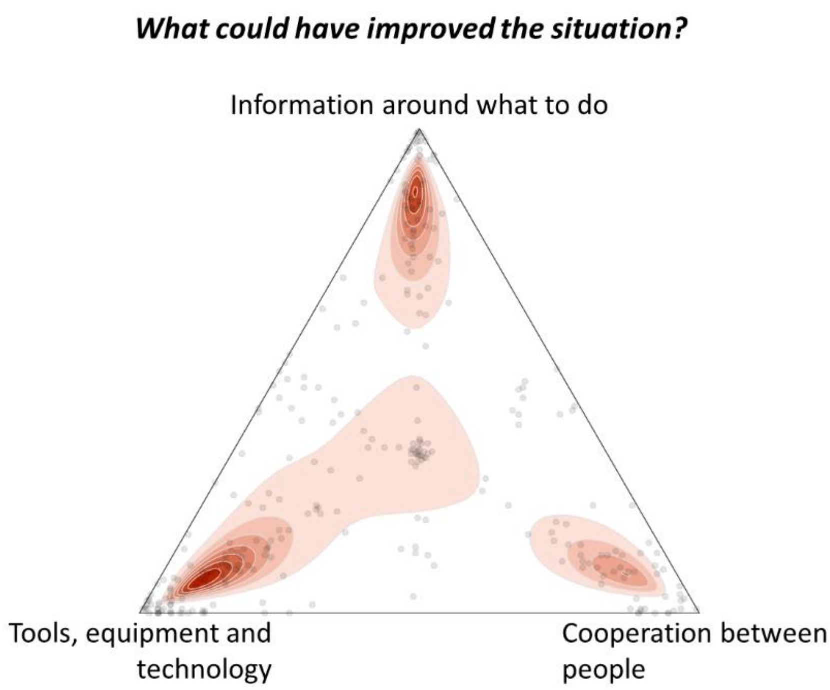

Figure 4.15. Improvement-oriented triad results.

4.4.3 Methodological results: capabilities, caveats, and multiple perspectives

While the spatial ethnographic data collection and analysis is at the core of this paper, it was found some noteworthy outcomes and insights regarding how the various data types and methods were combined. A primary finding related to inter-scale dynamics are the comparative differences in conclusions drawn from either aggregated variables or ethnographies and those drawn from an integrated approach. For instance, the priority for electricity as a critical service varies with different aggregation levels. Among regions with a very slow power network recovery index, the expectation would be a high value for improvements to electrical equipment or loss of power network services (Fig. 4.16). However, some narratives in these regions highlight composite struggles of loss of services, safety, and uncertainty, that aggregate geospatial methods do not uncover.

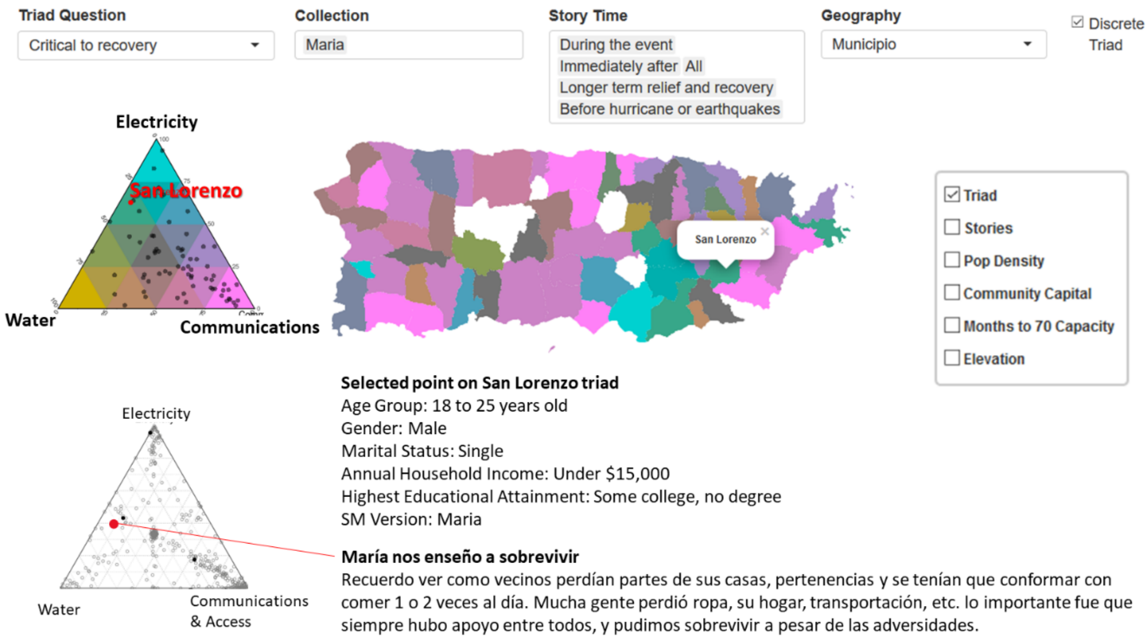

Figure 4.16. Screenshots of the geospatial application with critical infrastructure triad results. The top triad and map are color-coded with a tricolor scheme where discrete composite colors describe the balance between electricity (cyan), water (yellow), and communications (fuchsia) as critical to recovery. Points within the top triad represent geometric means of the signifier coordinates of data points within each municipality. The bottom triad pertains to data points within the selected municipality (i.e., San Lorenzo), where individual points pertain to specific responses shown in detail to the right when selected.

This multi-scale combination of indices and narratives shows that although an area may be ranked as having relatively minor resilience capacities when viewed from the top down, these are still areas where valuable capacities emerge that can be leveraged for resilience enhancement strategies. The previous examples described above from various micro-narratives show how community capital and infrastructure adaptation, modularity of local resources and equipment, and growth mindsets in the face of adversity occur in municipalities that are otherwise mapped as highly vulnerable and less resilient. These findings illustrate the complex and sometimes contested relationship between vulnerability and resilience, especially in terms of quantitative and geographic methods (Carvalhaes et al., 2021). For instance, a community may be vulnerable in terms of hazard exposure, enabling learning and self-sufficient capacities for resilience. However, such forms of resilience may be tragic in terms of poverty traps, for example, where vulnerable communities bear the burden of recovery (Bene et al., 2014).

Integrated analysis shows how quantitative trends can have exceptions and complexities. For example, narratives showing electric power as highly critical correlated with a slow energy recovery index also highlight the importance of local technical capacities such as gasoline and ice, together with critical burdens like safety and uncertainty for the safety of others. Overall, the results show how lived experiences associated with a place and time, in the form of ethnographic narratives, can be utilized together with other geospatial approaches to profile the kinds of dynamics that emerged from Maria.

4.5 Discussion & Emerging Insights

Generally, spatial ethnographic results and thick mapping align with other studies regarding the importance of communications systems regarding Maria in PR (Gay et al., 2019; Lopez-Cardalda et al., 2018; Pullen, 2018; Zorilla, 2017). However, results highlight two additional implications for communications: (1) nuances in the process of disaster management protocols can include lack of trust or access for public institutions and organizational capabilities, and (2) community impacts include the human burden of uncertainty and lack of information regarding the state of other family members, friends, and incoming aid.

As Puerto Rican authorities invest toward more resilient infrastructure systems, it is essential to note the increasing interdependencies of institutional structure and communications with other sectors. The efficiency and responsiveness of public institutions responsible for disaster aid were sometimes perceived as disorganized and chaotic. On one hand, such perceptions indicate the potential undermining of public uptake of future initiatives by such institutions due to lack of faith or reputation. On the other, it may suggest that organizational structure and leadership for critical services should be developed to be adaptable enough to shift between stable and unstable conditions and allow decentralized information flows and enough autonomy for operational personnel to respond quickly to real-time, on-the-ground conditions (McChrystal et al., 2015; Mintzberg, 1981; Ulh-Bien, 2007). For example, centralized decision-making and hierarchical organizational structures for power system management in PR could have created a critical interdependency and vulnerability to communications network failures, hindering information flows and recovery actions during the post-event phase.

Results highlight how natural and built environment variables manifest in personal narratives and how a thick mapping approach can be used for holistic analyses of disaster resilience toward unraveling the complexity of disasters and illuminating weak signals that cue future dynamics. For instance, the relationship between regions showing slow night lights-based electrical system recovery, triads highlighting critical services, and narrative descriptions show the range of human capabilities that power outages can hinder, such as using medical machines, contacting others, or mobility and access to backup power. Access to fuel for electrical generators and ice was a common theme for adapting and coping with the loss of critical services. However, getting to gas stations was sometimes complicated by long lines (Dorell, 2017; Gay et al., 2019). Ice served as a functional alternative to cooling to preserve food and medications. Such redundancies, especially when decentralized as stocks of ice and distributed energy generation, provide immediate relief while waiting for infrastructure recovery. In this way, the approach also identifies inherent capacities that can be further leveraged, such as infrastructure diversity and functional redundancy (Ahern, 2011; Biggs et al., 2012).

Modularity and local innovation were other capacities that emerged in personal experiences (e.g., mobile laundromat discussed in section 4.2). The wherewithal to power laundry machines locally and carry them in a pick-up truck displays how multifunctionality can be leveraged locally and creatively, especially when enabled by modular units and creative reuse of local capital (e.g., using idle buses as housing, or a pickup truck as a mobile laundry). Additionally, mobile units enable access by decentralizing where services are provided and at what times. Creative adaptations of local resources can be further understood, facilitated, and developed for future events (e.g., power generators in series). Resilience efforts can use such examples to proactively enable local innovations by highlighting key competencies like modularity, multifunctionality, and learning (e.g., Gilrein et al., 2019). In addition, there is something to be said about resilience as a mindset in the face of uncertainty as it relates to self-organized actions for adaptation and recovery.

It appears there is a range of attitudes between a growth mindset (i.e., disasters as an opportunity for learning, innovation, and improvement) and mental burdens associated with hurricane impacts (i.e., mental health and fear due to uncertainty and extended loss of communications). Previous research has highlighted the mental health impacts of Maria in PR (Orengo-Aguayo et al., 2019). Resilience literature in community psychology and education has highlighted the effects of a growth mindset on promoting resilience. In thisanalysis, this emerged primarily as characteristics for personal growth and helping others. Further work can explore how such mindsets relate to the capacity for innovation and proactive adaptation.

Results show that trust and uncertainty become a central part of community experiences upon disasters, especially when impacts are broadly severe and recovery is slow. It is difficult to discern if the lack of appeal to public institutions evident in the narratives was due to a lack of trust in government, powerful family and local community ties, lack of access, or a combination of these factors. However, some stories suggest a lack of faith in the capacity for institutions to effectively provide recovery services. Such sociocultural dynamics are significant in terms of Level II and Level III socio-technical complexity since technological solutions can be complicated by ineffective governance, lack of equitable access, and unintended consequences. For instance, while household generators and solar panels can ensure energy services upon disruptions of the centralized systems, programs that enable these resources may be untrusted, inaccessible, misused, and potentially dangerous (e.g., deaths have resulted due to carbon monoxide poisoning from generators).

4.6 Conclusions & Future Research

In terms of interdisciplinary research practice, it was found two beneficial pathways in integrating and maneuvering data that is disparate in quality (depth versus breadth) and type (subjective, objective) using the proposed approach:

1. The generation of more nuanced insights into the socio-technical dynamics for resilience enhancements in respect to the second and third levels of technological complexity.
2. The humanization quantitative variables and the development of a base (if not preliminary) understanding of what potential limits or unintended consequences may emerge from solutions drawn from technocentric or "objective" models.

It is a complex process to converge disciplines that have seemingly conflicting fundamentals and disparate methods, but thick mapping approaches from a complex systems perspective may offer a pathway toward accepting and synthesizing multiple perspectives to better match the complexity of the intertwined systems we observe upon disasters (Ashby, 1956; Naughton, 2017). While not as decisive and elegant as traditional approaches, it offers a way to "muddle through" complexity in the face of an accelerating, increasingly complex future (Allenby, 2012).

For resilience efforts in islanded communities like PR, it is essential to understand that complex systems are in constant flux (Cilliers, 2006). Since the beginning of post-Maria recovery and the work this paper is based on, PR has endured a series of compounding disasters, including earthquakes, drought, and dust storms during the currently developing COVID-19 pandemic. Given PR's geographic position and sociopolitical conditions, such circumstances set the island up for enduring concurrent crises that will require novel and agility-oriented approaches for community and infrastructure resilience (Carvalhaes et al., 2020). This study lays the groundwork for ongoing narrative collections along with other data that can be integrated over space and time to produce a dynamic and evolving picture of resilience in PR. Ongoing (re)analysis is then necessary for future resilience of PR as an islanded community (here referring to regions which access constraints, whether geographic, economic, or political), as are resilience measures that can be responsive to changing information and agile to changing socio-technical conditions.

A thick mapping approach has been applied to study resilience to Maria in PR. Further research is needed to continue to provide case studies that illustrate how such an approach can inform resilience theory and practice. This study attempted to augment spatial ethnographic approaches with more sophisticated geospatial methods, but there were quantitative limitations due to the spatial distribution and density of data points. Future work can aim to capture geo-statistically sound data for more comprehensive quantitative analysis alongside qualitative methods.

There is potential for thick mapping approaches to be particularly amenable to stakeholder and community interaction, co-production, and transdisciplinary research. Although it is beyond the scope of this paper, the effectiveness of making thick map research outputs like GeoApps available for iterative feedback, validation, and practical use by community participants and leaders is significant and should be explored. Subsequent case studies can evaluate how results from these types of approaches are used, how well outcomes from respective insights contribute to disaster resilience, and best practices for using thick mapping approaches in socio-technical resilience domains.

CHAPTER 5

CONCLUSIONS & SYNTHESIS

5.1 Summary

The preceding chapters have covered methods for developing social metrics in the form of Disaster Resilience Indices (DRI) and Social Hardship Indices (SHI) for engineering models of infrastructure reliability and resilience, and the implications for such indices in the face of urban complexity.

Chapter 2 demonstrated how social metrics could be used in a socio-technical network modeling framework of an electrical system and presented a novel method for developing a *TESHI* by leveraging the treatment-effect approach for H-Maria in Puerto Rico. The framework demonstrates how a social metric can be framed in terms of outcomes of human burdens toward reducing human hardships, rather than being framed around the ability to recover to normal community functions. The SHI methodology presents a way to attribute human hardships to specific disasters, and a method for weighting predicting factors of social hardship was presented. Results show that income and age are common factors for a series of hardship outcomes, including suicides, substance abuse, median house prices, and employment. An argument for social functions rather than metrics was presented.

Chapter 3 presents a critical review of DRI from a complexity perspective. Resilience principles were linked to tenets of complexity. It was found that DRI are becoming increasingly comprehensive, yet do not capture systemic aspects of urban systems such as polycentricity and diversity. Furthermore, DRI may be fundamentally misaligned with complexity paradigms by nature of reducing urban dynamics to a single metric.

Chapter 4 presented a novel methodology for integrating social complexity with performance-based metrics by leveraging distributed ethnographies and a thick mapping approach for Puerto Rico. It was found that individuals tended to bond with trusted friends and family, and sometimes bridge with other communities, rather than appeal to public institutions. Local innovation together with communitarian attitudes helped support adaptation and the substitution of infrastructure services. For interdisciplinary research, the proposed methodology offers a platform for integrating and maneuvering data that is disparate in quality (depth versus breadth) and type (subjective, objective), the humanization of quantitative variables, and the generation of nuanced insights into socio-technical resilience toward a base understanding of what potential limits or unintended consequences may emerge from solutions drawn from technocentric or "objective" models.

The next section will describe broader conclusions and implications for future resilience research in terms of connecting social dynamics to engineering assessments and capturing urban complexity.

5.2 Synthesis & Major Takeaways

5.2.1 Themes for Integrating Social Considerations and Technocentric Resilience Assessments

Between the literature and analysis associated with Chapters 2-4, andregarding efforts to develop interdisciplinary frameworks, integrated socio-technical models, and the ongoing shift toward a complexity paradigm, an emergent theme is that social considerations for otherwise techno-centric resilience assessments can take on general frames of reference in terms of the objectives, scope, and methods. In this sense, socio-technical integration for resilience assessments can be defined along the spectrum of conceptual frameworks that fall under impact-driven frameworks, complexity-driven methods, and community or stakeholder engagement (Fig. 5.1).

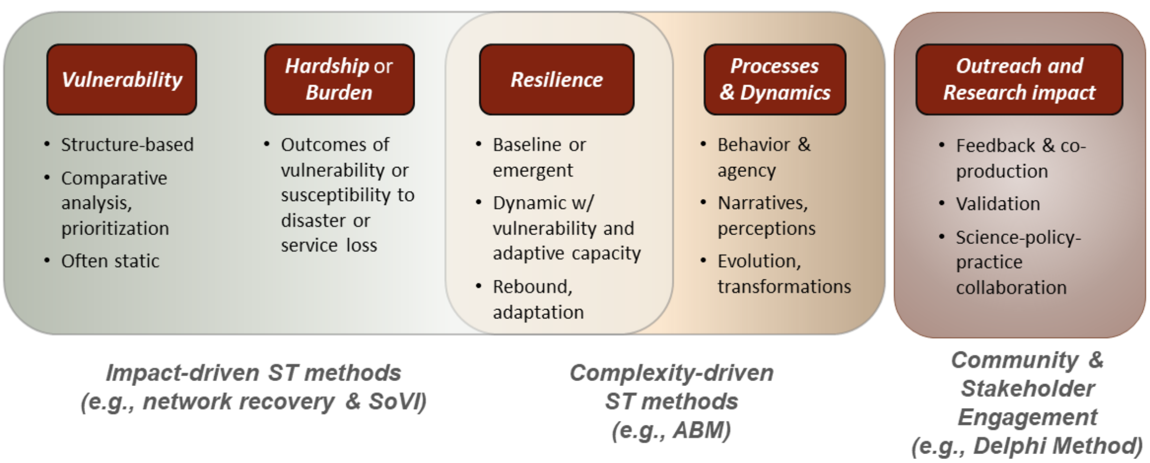

Figure 5.1. Conceptual approaches for coupled social and technocentric resilience assessments categorized as impact-driven, complexity-driven, and engagement. Red boxes indicate the conceptual driver for each type of approach, below which general attributes and applications are listed.

Impact-driven approaches are generally focused on snapshots of vulnerability and hardships based on sociodemographic and economic structures toward incorporating social elements (i.e., tend to be static temporally static) and can include indicators that compare community characteristics or quantify social burdens, such as in Chapter 2. These frameworks tend to be map-based snapshots, geographically explicit, and often hazard-agnostic, yet static in terms of time, space, and SETS interactions. Hardship-driven approaches aim to reduce specific disaster outcomes, such as mortality.

Complexity-driven approaches include community resilience approaches that are also based on snapshots but begin to consider indicators for adaptive capacities that have the potential to emerge upon a disaster, as discussed in Chapter 3. Approaches oriented around the concept of resilience begin to bridge static frameworks toward capturing understanding urban dynamics and attributes of urban systems that cue for the emergence of resilience. DRI, for example, can cue for key community attributes that indicate adaptive capacities (e.g., civic engagement), while still being spatiotemporally static, much like social vulnerability indices. However, frameworks explicitly oriented around complexity tend to focus on the processes and dynamics of socio-technical systems, and fundamentally depart from impact-driven assessments. This can be captured with methods like agent-based and dynamic modeling to simulate interactions and the behavior of systems over time. Alternatively, complexity-driven assessments can aim for qualitative insights that indicate the potential emergence of community resilience, as demonstrated in Chapter 3.

Lastly, engagement represents a “meta” dimension to resilience research, critical for community feedback, data pathways and experimentation, maintaining the relevance of use-based research projects, and interfacing science and policy for improved disaster outcomes. However, engagement can also be leveraged for expert-driven quantitative assessments such as the Delphi and scorecard methods (e.g., Berke et al., 2015; Gimenez et al., 2017).

It is important to define what is meant by social considerations in the collaborative resilience assessment of engineered systems. Large scale resilience research collaborations should take account of each type of method (impact-driven, complexity-driven, and engagement approaches) for a complete as possible interdisciplinary front for effective research outcomes, if not to at least be explicit in which aspects of social considerations are included. Impact-driven frameworks have been widely used to capture the "pulse" of a system given a specific system framing, or to measure outcomes and respective drivers of social impacts, given a specific event. On their own, however, impact-driven frameworks may be too spatiotemporally static and narrow in the face of future accelerating change and uncertainty, whereas complexity-driven methods can capture key dynamics and weak signals to qualify and add nuance to more reductive, impact-driven frameworks. Engagement also is key to maintain researcher knowledge of the continuously changing dynamics as systems evolve and should ideally feedback into mixed-methods approaches.

5.2.2 Space and Place as Anchors for Multiple System Framings

Given that there are multiple ways and scopes to frame a system, especially given the different disciplinary and sociocultural meanings that may be simultaneously present, the geographic and anthropological concepts of space and place can serve as anchors to integrate multiple system framings. There are two major advantages to leveraging these concepts: (1) capturing multiple system framings to better capture complexity, and (2) capturing contested sociocultural meanings and futures associated with a system.

Regarding the first, for example, the Thick Mapping approach in Chapter 3 combines individual experiences and quantifications of coded narratives with aggregate sociological views of community resilience via DRI that are similar to the impact-driven approach in Chapter 2. In this way, multiple disciplinary perspectives and scales of the social domain are captured within a space, such as a municipality or energy network management regions (i.e., multiple places within the same spaces). Any framing of a complex system is inherently a partial reduction of the "true" system, but integrating multiple perspectives are necessary toward "complete enough" system representations and can inform more holistic solutions that better match the complexity of urban systems (Allenby, 2012; Ashby, 1956; Cilliers et al., 2013).

Regarding the second advantage, that the dynamics of urban systems work along space and time is often implied in resilience assessments. However, given social complexity, there is a third and often overlooked plane of urban dynamics: evolving sociocultural meanings that drive decisions, actions, and interactions in a system (i.e., place). As shown in the case of Puerto Rico and Hurricane Maria, relevant sociocultural dynamics for urban system resilience include trust in governance and public institutions, as will be further described below. From a SETS perspective, capturing the more elusive sociocultural dimension is a key contribution of social and complexity sciences to traditional technocentric assessments. The concepts of place and thick mapping can be leveraged toward new interdisciplinary frameworks as a way to “tap in” to eminent sociocultural changes that drive urban system dynamics.

5.3 System Boundaries & Limitations

5.3.1 System Framing & Concurrent Disasters in the 21st Century

The scope of the work described in this dissertation, and the larger project this research is a part of, bounds Puerto Rico as a system in a limited way. Nonetheless, dynamics that are exogenous to the framing of this system can have significant outcomes. Namely, sociopolitical and technological dynamics and concurrent disasters in Puerto Rico are outside of the scope of this research yet have had relevant implications for the energy system since the onset of the project.

Since the beginning of the effort and initial design of the research outlined in this document, critical events have continued to occur in Puerto Rico that introduce further complexity and challenge the initial system framing and boundaries in question in the preceding chapters. Several disastrous events have inflicted PR, including earthquakes, drought, dust storms, infrastructure cyber attacks, and the global COVID-19 pandemic (Carvalhaes et al., 2020; Poteet, 2020). Social unrest and political change have also developed in reaction to the recovery policies and circumstances that have unfolded since H-Maria made landfall on September 20th, 2017. For example, public masses have taken to the streets demanding the resignation of Governor Rosello due to his alleged corruption and continued ineffectiveness toward the recovery and resilience of Puerto Rico in the aftermath of Maria (Robles & Rosa, 2019). Therefore, the ground truth of the system as the object of inquiry has not only been in constant flux but has experienced noteworthy disastrous perturbations that have relevance to the general resilience of Puerto Rico.

This dissertation focuses on resilience specific to hurricanes, but it is necessary to consider potential trade-offs and caveats regarding more general resilience. Such specified resilience gears toward foreseeable risks in terms of a specific challenge (i.e., future hurricanes), whereas general resilience refers to the overall capability of systems to adapt or transform in response to various types of shocks, including unprecedented events (Folke et al., 2010; van der Merwe et al., 2018). Trade-offs can exist when enhancing specified resilience, which could mean there are important investments and efforts for Puerto Rico. Understanding the general resilience of the island, especially considering a future of uncertainty, is a challenging goal to bound and an undertaking of extensive scope. However, it is possible to maintain a framework that adheres to the intent of specified resilience while acknowledging limitations in the system framing (social, ecological, and technological components considered, the respective boundaries, spatial and temporal scales, and relationships). Additionally, outlining what some of the broader implications may be as they emerge throughout the research process can be beneficial to this end. First, it is essential to understand the system framing, insights, and scope of each approach taken in this dissertation.

Chapter 2 offers insights specific to social hardships faced by Maria, thus assuming a system framing that excludes the rapidly developing sociopolitical conditions and the dynamics of the then soon-to-come global COVID-19 pandemic. The pandemic has shown how resilience to disasters can range not only temporally from disruption to post-recovery phases (Reddy, 2020), but categorically from momentary disruptions, such as a power component failure due to wind gusts, to extended and “rhythmic” disruptions like the COVID-19 crisis, which occurs in successive waves. These dynamics have rendered many widely adopted indicators became largely obsolete in indicating assets and capacities that emerged as critical during the pandemic, such as tele-access, the ability to isolate cases of infection, and multi-modal transportation (Amekudzi-Kennedy et al., 2020; Woods et al., 2020).

The thick mapping approach in Chapter 4 represents a more holistic and broad undertaking, though still focused on Maria. However, the framework has potential for longitudinal analysis and a multi-hazards perspective since data collection has continued through 2020. Two additional deployments of the data collection tool were done: (1) A second narrative collection regarding individual experiences that are coded as related to H-Maria, the 2020 earthquakes, or both the latter events; and (2) a narrative collection effort related to COVID-19, which is currently under development. The latter two datasets were not included in the thick mapping analysis due to the scope of the analysis and its intent as contributing to a methods paper based on Maria as a case study. However, it was intended that the thick mapping, in the form of an online digital geographic application, is amenable to being enhanced further with temporal sequences and the capability to incorporate additional layers, including model outputs and filterable narrative collection datasets. Such capabilities enable a follow-up analysis that can address current limitations.

Rather than particular classes of urban system assets and characteristics (such as with DRI and indicators), elements that pertain more closely to general resilience, such as leadership capacities and organizational structures, emerged as critical during the

COVID-19 crisis (Allenby & Chester, 2020). Carvalhaes et al. (2020) have highlighted lessons from COVID-19 that did not or likely will not emerge from the indicator and modeling methods in the preceding chapters, such as the potential for concurrent hazards, the dynamic nature of criticality, the trade-offs between resilience and efficiency, and the role of leadership and the ability to shift organizational modes between stable and unstable conditions.

Concurrent hazards are a clearly relevant theme for Puerto Rico. Long-term recovery efforts related to Maria have gone underway amid dust and drought conditions, and a recently discovered fault line near the Southwest coast of the island is causing frequent and sometimes intense earthquakes (USGS, 2020). Not only must municipalities, communities, and infrastructure endure the additional stressors and socioeconomic costs to cope with and endure multiple hazards, the pandemic presents atypical challenges compared to other types of disasters, like widespread and sustained unemployment (Rosa & Robles, 2020). Furthermore, the pandemic has undercut community disaster resilience capacities (e.g., income, health insurance), and assets like disaster centers and emergency shelters, common indicators of community resilience, have become problematic as they contradict limitations for social aggregation (i.e., social distancing).

Days after the transition toward Luma as the primary energy infrastructure provider, a cyberattack produced 2 million hits per second in the company’s applications, which happened shortly before an explosion at a power station left hundreds of thousands of residents without power (Nash & Rundle, 2021). Municipal leaders have had to deploy independent recovery efforts, and residents claim dealing with similar conditions

Hurricane Maria (Coto, 2021). These ongoing occurrences demonstrate the changing landscape of infrastructure vulnerability and resilience with the accelerating integration of cyber technologies into physical infrastructure systems (Chester & Allenby, 2020).

The concurrence of hazards has shown some positive outcomes that cue for emerging resilience capacities, however, such as a culture of learning from past failure and success. For example, having endured treatment interruptions, limited transportation, and scarce equipment and medicine, clinicians in Puerto Rico developed practical emergency measures that paid off during COVID-19 to maintain functions and contain the virus among vulnerable patients (Gay et al., 2019; Rivera et al., 2020). Facing concurrent hazards can present competing demands and resource scarcity among disasters, which suggests that rather than hardening infrastructure for improved robustness to specific hazards, a multi-hazards approach focusing on agility to unforeseen types and combinations of hazards can be beneficial toward building infrastructure resilience (Ryan, 2009), as may be the case for Puerto Rico. Capacities like creatively leveraging multifunctional assets and flexibility can enable infrastructure to shift functions and extend operability in the face of unprecedented disasters (Gilrein et al., 2019), but are not necessarily captured by the previous chapters.

In terms of criticality, the term traditionally refers to an industry and defense definition of Critical Infrastructure (CI), such as energy and water assets and systems, which are deemed vital to economic security and public health and safety (*DHS*, 2020). However, such a framing of criticality does not consider the differences between hazards and emerging interdependencies for infrastructure. For example, healthcare infrastructure depends on supply chains for personal protective equipment (PPE), and parks, which typically are not considered CI, have emerged as critical by serving as field hospitals, alternative sheltering, and public emotional and physical well-being (Fink, 2020; CDC, 2020; Welsh, 2020). To account for dynamically changing demands for infrastructure services and functions among and between hazards, a framing of criticality that reflects such changes and ranks criticality based on critical human capabilities (the set of valuable functions an individual effectively has access to) may be more appropriate given the pandemic and the future threat of concurrent hazards (Clark et al., 2018). Treating criticality as dynamic and based on critical human capabilities (e.g., such as those ranked by Maslow's hierarchy of needs), along with infrastructure and institutional flexibility, can enable infrastructure resilience against a variety of hazards and their combinations. The role of criticality and CI in Puerto Rico given Maria, the 2020 earthquakes, and the COVID-19 pandemic is one area of inquiry that can be further outlined toward future research.

Infrastructure systems traditionally emphasize efficiency (i.e., optimizing for stable systems and environments to reduce waste, time, effort, and resources) at the cost of resilience (i.e., investing in increased "slack" for unstable systems and environments to enable redundancy, diversity, and adaptation – otherwise considered waste), a seemingly unavoidable tension between goals (Allenby and Chester, 2020; Martin, 2019; Tenner, 2020). In Puerto Rico, for instance, energy transitions are a key consideration, such as aiming for 100% solar energy generation (e.g., Arduengo, 2020, Heard et al., 2017), for example, which would reduce greenhouse gases that contribute to future climate hazards and provide decentralized energy services. Solar energy as a form of distributed generation and point-source consumption offer some resilience-related benefits such as the limitation of cascading network failures, and mobility and modularity (both in governance and networked components) associated with the technologies that enable flexibility and access to energy services. However, a system relying exclusively on (or overwhelming so) one type of energy infrastructure may be inherently vulnerable (e.g., economic fragilities) and lacks diversity, a resilience principle (Biggs et al., 2011; Heard et al., 2017). Implications of working scenarios for Puerto Rico's future electrical system (and as these scenarios may be modeled in Chapter 2), in terms of resilience and efficiency, ought to be considered and highlighted in terms of stakeholder aims toward resilience and sustainable development.

Lastly, the ability to shift organizational modes between times of stability, where traditional bureaucratic structures enable quick decisions (i.e., Administrative Leadership), and times of instability, where there is a need for flexible decision making and creativity in the face of complex and rapidly evolving conditions (i.e., Adaptive Leadership), may have salient implications for Puerto Rico as it faces future climatic and biophysical threats (Ulh-Bien et al., 2007). Ulh-Bien et al. (2007) have outlined the concept of Enabling Leadership as a form of organizational structure that enables the shifting from administrative to adaptive leadership modes. For Puerto Rico, it appears there may have been an obstinate reliance on a leadership structure centralized in San Juan (i.e., administrative), which was disrupted by failed communications systems. Such an institutional setup and subsequent failures to adapt can impact the adaptive capacity and recovery rates (i.e., resilience) of infrastructure systems as on-the-ground technicians lack the communications and authority necessary, despite being proximal to potential solutions. A clear protocol for adaptive leadership could have been in place, such that when the traditional administrative structure (hierarchical bureaucratic decision making and information sharing) is interrupted, there is a modular, decentralized, or autonomous capability (i.e., an institutional micro-grid or "team of teams") that is enabled (McChystal et al., 2015).

5.3.2 Governance, Institutional, & Sociocultural Dynamics

The public infrastructure providers, formerly the public agency PREPA, have now been changed to Luma in a public-private partnership with PREPA. The Puerto Rican government has chosen to privatize the energy system and rebuild it in a centralized and fossil-fuel-oriented fashion, rather than incorporating renewables and decentralized capabilities that can be more advantageous for ST resilience. This change has rendered both continuing and new vulnerabilities in terms of the energy system as Luma faces heavy criticism since formally taking over the electrical system.

The energy transition in Puerto Rico has been primarily driven by political and financial services and can have profound implications for energy access, ongoing corruption, and civil instability (Garcia, 2021). An independent report by the Institute for Energy Economics and Financial Analysis (IEEFA) determined that the Luma contract will result in increased electricity rates, use companies with insufficient financial capabilities, promote the expansion of outdated natural gas plans, pursue unsound labor practices, allow less public input, and altogether repeat past mistakes (Sanzillo, 2021). The report concludes that, "The LUMA contract is objectionable on a mix of policy and procedural grounds that are so extensive that its execution is unlikely to achieve critical resiliency, affordability, renewable energy, workforce, and budgetary goals." Sanzillo

(2021) and others also point that the Luma contract lacks oversight and enables further costs that go to fossil fuel interests, bondholders, debt service, political patronage, and bad contracting (Garcia, 2021; Walton, 2021). Residents and workers unions have been protesting and taking direct action against the Luma agreement demanding the contract be rescinded, resulting in riot police forcefully dispersing the crowd (Orlando Delgado Rivera, 2021).

Cultural attributes and dynamics that are beyond the scope of this dissertation are not limited to distrust and unrest. For example, the so-called *Puerto Crypto*, a movement toward creating a Caribbean crypto-utopia, is said to be capable of transforming Puerto Rico into the next Hong Kong by igniting a trillion-dollar market and transforming its economy (Klein, 2019). Puerto Rico's economic policies are already laying heavy incentives for the cryptocurrency and blockchain industries, which can have significant implications for energy dynamics, cyber vulnerability, extant sociopolitical stresses, and socioeconomic change (Crandall, 2019). In this way, Puerto Crypto can be viewed as one of the harbingers of eminent Anthropogenic changes in Puerto Rico. Still, there are other cultural aspects at play not captured in the scope of this dissertation, which can range from place attachment to religions and traditions that bind communities together in times of crisis.

5.4 Broad Implications & Pathways for Collaborative Resilience Research

Interdisciplinary resilience research can link multiple knowledge-based and practice institutions (e.g., universities, NGOs, utilities) within a common project that aims to assess resilience and make recommendations for interventions in urban systems. Such projects are here referred to as Large-scale Resilience Collaborations (LRC), such as the project based on the NSF-CRISP grant toward Enhancing Resilience in Islanded Communities (ERIC) that the work in this dissertation is a part of, for example. Given the unfolding events and research limitations described in section 3, there are three major factors that have significant implications for LRC in providing impactful insights and recommendations for decision-makers:

i. The scope of LRC is necessarily partial. However, overlooking institutional dynamics and critical aspects in the sociopolitical dimension can undermine subsequent recommendations and decision-making tools.

ii. The system being analyzed has the capacity to evolve much more rapidly than what LRC can respond to. In respect to analyzing Hurricane Maria in Puerto Rico, concurrent disasters and sociopolitical dynamics challenge the narrow view of focusing on hurricane resilience.

iii. It is essential for LRC to adequately connect with the institutions and leadership that drive adaptations (or lack thereof).

In respect to the above items, Luma's efforts to rehabilitate the PREPA electrical grid, rather than transition to renewables or partially decentralized options to enhance energy resilience like mini-grids, not only undermines the islands previous goals of reaching 100% renewable energy generation by 2050, but shows the potential misalignment of LRC efforts in having a significant benefit for Puerto Rico. As of yet, there appears to be little to no evidence that there is any input from the vast research efforts surrounding resilience in Puerto Rico after Maria (Sanzillo, 2020). For example, models that inform the selection of transmission lines to be hardened to reduce human hardships (Chapter 1), or studies that suggest creating functional redundancies or diversity of capabilities that can be substituted (Chapter 2-3). The sociopolitical changes described above will also, in return, affect future resilience research. For instance, the privatization of the energy system has the potential to make obtaining research data more difficult since the confidentiality and proprietary obligations of Luma as a corporation restricts the availability of public information (Sanzillo, 2021).

In terms of partial system framing and connecting with institutions, there is a lingering need to leverage the transformation of infrastructure governance for resilience in the Anthropocene (Chester, Miller, Munoz-Erickson, 2020). Institutions and their embedded values, norms, and processes can keep infrastructure obdurate, or enable transformation. For Puerto Rico, it appears the case is that decision-making institutions are in many ways locked-in to “business as usual” for infrastructure investments and management. Along with technical assessments, future resilience efforts should then focus on identifying leverage points within institutions that manage and design infrastructure in the island toward facilitating the necessary transformations toward a more resilient future for the island. Connecting to the right institutions and leadership to mobilize knowledge effectively toward resilience and sustainability transitions needs to be a concerted effort for collaborative resilience research.

In this context, scientists and engineers are part of the systems they are studying in that they have the potential to affect and be affected by SETS dynamics (Allenby, 2012). A problem occurs if this is not sufficiently recognized so that research becomes detached from the institutions and actors that drive the system. For example, as the ground truth of the system changes while research progresses, scientific efforts can become obsolete before they have been completed. One answer to this problem is that research should itself be dynamic and reflexive as researchers interact with the system. To this end, resilience research should focus on processes rather than definitive end points, and tolerate intermediate deliverables and failed attempts to reward experimentation, innovation, and reflexivity that enable relevant and impactful outcomes, rather than measuring research success by quantity and timeliness of deliverables (Chester et al., 2021; Davidson et al., 2007; Ferris, 2020; Kerzner, 2017).

In the Anthropocene, infrastructure will need to be mediate human-environment interactions in light of rapidly accelerating cybertechnologies, unstable climates, and sociopolitical stresses and disruptions (Chester et al., 2021). Future research should reflect these conditions and be adaptive and flexible enough to remain relevant and support the necessary infrastructure capacities. Given these eminent future conditions, weak signals need to be managed alongside risk analysis and reductive approaches like DRI and performance-based metrics. There is usefulness for metrics like indices in that they enable pragmatic and easily understandable analysis for practitioners and stakeholders. However, on their own, they tend to be narrow in their systems-framing, which may result in missed signals of oncoming change and overlooked social dynamics that can undercut subsequent strategies. For example, the lack of government appeal observed in Chapter 3 can be observed as a weak signal for the protests and unrest that is now unfolding, and a lack of trust public-private techno-centric solutions since the Luma contract began.

Lastly, since infrastructure in the Anthropocene needs to be agile and flexible in the face of accelerating change and uncertainty, interdisciplinary research will need to better connect this to social dynamics and science-policy engagement strategies. In other words, what will adaptive infrastructure mean for communities in places like Puerto Rico, and what kind of assets, capacities, and knowledge will be necessary at the local level when agile systems are responding to disruptions? These questions can be posed for future collaborative resilience projects toward bridging the gap between academic research and on-the-ground decision-making, planning, and community resilience.

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APPENDIX

APPENDIX A

DEVELOPING A BASELINE RESILIENCE INDEX FOR DISASTERS IN PUERTO RICO

The following is based on a white paper by Thomaz Carvalhaes last revised on June 6th, 2021.

Objectives

Climate disasters continue to pose significant challenges to critical infrastructure systems. The catastrophic impacts and rapidly cascading infrastructure failures due to Hurricane Maria in Puerto Rico demonstrate the increasing necessity to understand infrastructure interdependencies. Such islanded communities are particularly vulnerable due to intermittent and limited connectivity to external supporting systems. Because hurricanes and other disasters will continue to occur, it is important to understand infrastructure and social vulnerabilities that contribute to failures, impacts, and recovery, and work toward enhancing the resilience of critical infrastructure systems and affected communities.

Based on this motivation, a primary objective of the ERIC project (Enhancing Resilience in Communities) is to develop a data-driven modeling framework to understand both physical and social vulnerabilities and inter-dependencies in islanded communities, with Puerto Rico (PR) acting as a case study. A social-technical power network model can aid in assessing existing preparedness (i.e., “inherent resilience”), and evaluate and implement resilience-enhancing measures through multistakeholder engagement and engineering analysis. Such an approach extends engineering resilience to account for other social elements and recognizes that human and technical systems are interdependent.

Background

While a climate disaster such as a hurricane may impact an entire region, different communities within this region may be impacted differentially. This can be due to either a difference in physical vulnerabilities (e.g., exposure of local power lines to destructive factors of a hurricane like wind speed and falling trees) or to social vulnerabilities (e.g., financial preparedness to cope with the damages). While vulnerability is normally described as a function of exposure and sensitivity to a disaster, resilience is more closely related to the degrees of adaptive capacity a community or infrastructure system has to cope and recover from a disaster (Cutter, Boruff, & Shirley, 2003; Engle, 2011; Holling & Gunderson, 2002; Nelson, Adger, & Brown, 2007; Smit & Wandel, 2006).

In a simulation of a power network, the vulnerability of technical components and resilience of the system can be modeled with probability-based fragility functions and metrics such as demand, capacities, loads, and repair time/cost (e.g., Vugrin, Turnquist, & Brown, 2014). However, metrics that represent social vulnerability and resilience are less clear-cut.

Myriad methods are currently established for assessing vulnerability and resilience of communities to climatic and environmental disasters (e.g., Cutter, 2016; NIST, 2015; Johansen et al., 2017). The methods vary in terms of breadth, data types, and application. For example, some methods can be categorized as *community-level* resilience metrics as they are derived (and often subjectively by way of community-participation) specifically for a geographical community context (Johansen et al., 2017). Other methods are *sector-specific*, such as building codes and other structures that directly affect human health and well-being upon a disaster. Lastly, *sociological* methods leverage quantitative data including economic and demographic metrics indicative of the resilience of a community (e.g., social connectivity, health coverage, disabilities).

Two significant advantages of the latter methods are data availability, ease of quantification and visualization to a variety of stakeholders, and generalizability to other [islanded] communities. Thus, this project focuses on two widely adopted sociological methods for resilience metrics to marshal for a power network model: The Social Vulnerability Index (SoVI), and the Baseline Resilience Index (BRI). The SoVI is a popular product from the Hazards and Vulnerability Research Institute (HVRI) and is already available at the Municipio level for PR. Meanwhile, the BRI has only been developed for the Southeastern United States. Therefore, the main objective of this report is to describe the construction of a BRI for the island of Puerto Rico.

Whereas the SoVI is useful for assessing the vulnerability of a community and as a planning tool, the BRI is more appropriate to measure the resilience of a community over time (Cutter, Burton, & Emrich, 2010; Johansen et al, 2017). Hence, it is more appropriate for a project aiming to develop measures to *enhance* the resilience of islanded communities by first assessing the current or inherent resilience of the region, which facilites the identification of factors that can be improve resilience, and then enabling future BRI assessments that can compare to previous resilience baselines.

Methodology

Overview

The BRI for PR was constructed following the methodology outlined by Cutter, Burton, and Emrich (2010) and Flanagan et al (2011). The key element of such indices are that they are place-based. Since a technical power network can be represented by nodes in a network that correspond to *in situ* components in known geographic locations (e.g., a power plant, a major transformer), social factors can be linked to these nodes according to which municipalities they impact. For PR, the BRI will be done by Municipio (assigned as "county" in Census databases) due to both data availability, compatibility, and relevance to stakeholders and decision-makers.

While the SoVI and BRI have very similar methods both developed by HVRI, there are a few significant differences. The BRI uses more than twice the variables (36 total) as the SoVI (15 total), which extend beyond solely Census data to several disparate sources. Additionally, the BRI is composed of 5 subindices: social resilience, economic resilience, institutional resilience, infrastructure resilience, and community capital, each with a set of respective variables. The variables of the subindices are averaged together to reduce the affect of differing amounts of variables for each subindex. The numbers for each subindex are then compounded additively into a resilience index that ranges between 0 and 5, where 5 is the most resilient. This is another difference between SoVI which is entirely additive and scaled from 0 to 1.

Data and Calculations

Data for the BRI relies heavily on Census county-level data, but includes several variables obtained from FEMA databases, North American Industry Classification System, city and county databooks, and other sources that provide per-municipality data. Some of the variables require short calculations or normalization of the original data, and it was found that some sources outlined in the technical document did not have data available for PR, in which case data was substituted from other sources (*see* Appendix for a table describing the variables for each subindex, data sources, and respective calculations). Once the variables are gathered, the values for each variable x_i are scaled to range between 0 and 1, where 1 is the most resilient using a Min-Max rescaling:

$$\frac{x_i - min}{max - min}$$

The rescaled variables for each subindex is then averaged to produce a score for each of the five major subcomponents of resilience in the BRI framework. Lastly, the five scores are aggregated additively with equal weight to produce the final BRI. Because the BRI is geographically explicit, results can then be mapped and overlain by the power network to assign metrics to each node of the network model.

Table A.1. Data used for BRIC-PR

Category	Variable	Data Source in Cutter et al., 2016	Data Source Used	Calculation (if applicable)
Social Resilience				
Educational equity	Ratio of the pct. population with college education to the pct. population with no high school diploma	US Census 2000	ACS17 - 5 Year	(% bachelor's degree or higher)/(100 - % high school graduate or higher)
Age	Percent non-elderly population	US Census 2000	ACS17 - 5 Year	None
Transportation access	Percent population with a vehicle	US Census 2000	ACS17 - 5 Year	(Total Households - Housholds w/ No vehicle available)/Households
Communication capacity	Percent population with a telephone	US Census 2000	ACS17 - 5 Year	(Owner occupied: With telephone service available + Renter occupied: With telephone service available)/Total Households
Language Competency	Percent population not speaking English as a second language	US Census 2000	ACS17 - 5 Year	% speak English only or speak English "very well"; Estimate; Population 5 years and over
Special needs	Percent population without a sensory, physical, or mental disability	US Census 2000	ACS17 - 5 Year	100 - % with a disability; Estimate; Total civilian noninstitutionalized population
Health coverage	Percent population with health insurance coverage	US Census 2000	ACS17 - 5 Year	% Private Coverage; Estimate; Civilian noninstitutionalized population
Economic Resilience				
Housing capital	Percent homeownership	US Census 2000	ACS17 - 5 Year	Owner occupied/Total Population in Housing Units
Employment	Percent employed	US Census 2000	ACS17 - 5 Year	Employment/Population Ratio; Estimate; Population 16 years and over
Income & equality	GINI coefficient	Computed from US Census 2000	American FactFinder	None
Single sector employment dependence	Percent population not employed in farming, fishing, forestry, and extractive industries	US Census 2000	ACS17 - 5 Year	Total - Agriculture, forestry, fishing and hunting, and mining/Total Civilian employed population 16 years and over

Employment	Percent female labor force participation	US Census 2000	ACS17 - 5 Year	None: Percent Female; Estimate; Civilian employed population 16 years and over
Business size	ratio of large to small businesses	County Business Patterns (NAICS) 2006		
Health access	Number of physicians per 10, 000 population	US Census 2000	ACS17 - 5 Year	Healthcare support occupations/Civilian employed population 16 years and over
Institutional Resilience				
Mitigation	Percent population covered by a recent hazard mitigation plan	Fema.gov		
Flood coverage	Percent housing units covered by NFIP policies	bsa.nfipstat.com		
Municipal services	Percent municipal expenditures for fire, police, and EMS	USA Counties 2000	ACS17 - 5 Year	
Mitigation	Percent population participating in Community Rating System for Flood (CRS)	Fema.gov		
Political fragmentation	Number of governments and special districts	US Census 2002		
Previous disaster experience	Number of paid disaster declarations	Fema.gov		
Mitigation and social connectivity	Percent population covered by Citizen Corps programs	citizen.corps.gov		
Mitigation	Percent population in Storm Ready communities	stormready.noaa.g ov		
Infrastructure Resilience				
Housing type	Percent housing units that are not mobile homes	US Census 2000	ACS17 - 5 Year	Total Housing Units - Structure: Mobile Homes
Shelter capacity	Percent vacant rental units	US Census 2000	ACS17 - 5 Year	
Medical capacity	Number of hospital beds per 10,000 population	American Hospital Directory www.ahd.com		
Access/evacuati on potential	Principle arterial miles per square mile	GIS derived from National Atlas.gov		

Housing Age	Percent housing units not built before 1970 and after 1994	City & County Databook 2007		
Sheltering needs	Number of hotels/motels per square mile	County Business Patterns (NAICS) 2006		
Recovery	Number of public schools per square mile	Gnis.usgs.gov		
Community Capital				
Place attachment	Net international migration	census.gov		
Place attachment	Percent population born in a state that still resides in that state	US Census 2000	ACS17 - 5 Year	
Political engagement	Percent voter participation in the 2004 election	City & County Databook 2007		
Social capital-religion	Number of religious adherents per 10,000 population	Assn. of Religion Data Archives		
Social capital-civic involvement	Number of civic organizations per 10,000 population	County Business Patterns (NAICS) 2006		
Social capital-advocacy	Number of social advocacy organizations per 10,000 population	County Business Patterns (NAICS) 2006		
Innovation	Percent population employed in creative class occupations	USDA Economic Research Service ers.usda.gov		

Preliminary Results

The resulting index was mapped by municipality for mainland Puerto Rico, which includes 76 of the 78 municipalities (i.e., excludes the small islands of Culebra and Vieques which are not part of the centralized electrical network) (*see* Fig. 1). Working results show that the five municipalities vary at both the sub-index and overall BRI level (Table 1), with a 30% difference between San German and Mayaguez for the BRI. It is noteworthy that infrastructure resilience was calculated to be significantly higher than social and economic resilience for all five municipalities. At the same time, Hormigueros, Rincon, and San German scored very high for infrastructure resilience whereas Mayaguez scored much less. Such results may reflect current emphasis on resilience for infrastructure rather than communities and could be used to suggest which municipalities are in greater need of infrastructure improvements or social programs.

Table A.2. Preliminary results for BRI for five selected municipalities in West Puerto Rico.

		Anasco	**Hormigueros**	**Mayaguez**	**Rincon**	**San German**
Sub-index	Social Resilience	0.36	0.43	0.41	0.49	0.55
	Economic Resilience	*0.46*	*0.55*	*0.46*	*0.57*	*0.56*
	Institutional Resilience	TBD	TBD	TBD	TBD	TBD
	Infrastructure Resilience	0.65	0.79	0.55	0.94	0.97
	Community Capital	TBD	TBD	TBD	TBD	TBD
Baseline Resilience Index		1.47	1.78	1.41	2.00	2.09

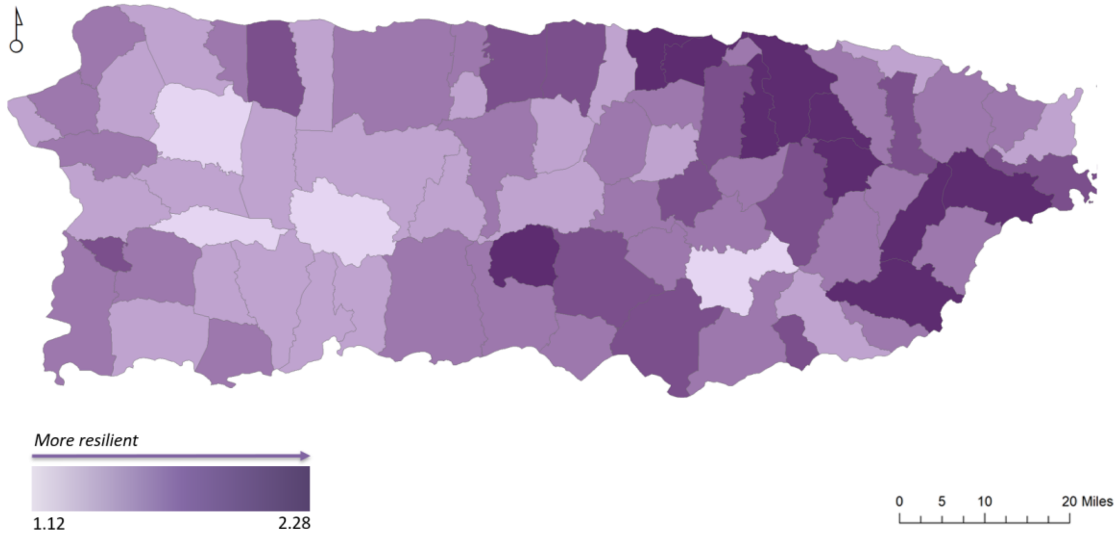

Figure A.1. Baseline Resilience Index for Puerto Rico (BRI-PR).

Interesting metrics are also observable by looking at each resilience subindex. Table 2 highlights the variables of the first two categories. It is notable that social resilience contains seven variables, while economic resilience contains only 6, so averaging the variables does reduce the influence of this disparity. However, the range and variability of the variables is overlooked in this way, such as with Rincon which has very high scores for many variables, and only a few very low scores that bring the mean down substantially. Therefore, as a tool it may be useful to use the BRI as a compound metric but also to observe the components of each sub-index in order to better understand which factors may be contributing to the enhancement or reduction of resilience.

Table A.3. Scaled metrics of selected BRI categories.

Variable	Anasco	Hormigueros	Mayaguez	Rincon	San German
Social Resilience	***0.36***	***0.43***	***0.41***	***0.49***	***0.55***
Ratio of the pct. population with college education to the pct. population with no high school diploma	0.14	0.70	0.71	0.43	0.53
Percent non-elderly population	0.36	0.00	0.05	0.01	0.03
Percent population with a vehicle	0.81	0.45	0.08	0.32	0.13
Percent population with a telephone	0.49	0.62	0.39	0.90	0.87
Percent population not speaking English as a second language	0.43	0.74	0.79	0.97	0.60
Percent population without a sensory, physical, or mental disability	0.18	0.08	0.19	0.05	0.90
Percent population with health insurance coverage	0.06	0.44	0.64	0.77	0.82
Economic Resilience	***0.46***	***0.55***	***0.46***	***0.57***	***0.56***
Percent homeownership	0.91	0.60	0.05	0.82	0.40
Percent employed	0.77	0.62	0.29	0.60	0.39
GINI coefficient	0.04	0.18	0.99	0.23	0.78
Percent population not employed in farming, fishing, forestry, and extractive industries	0.53	0.71	0.68	0.73	0.31
Percent female labor force participation	0.17	0.97	0.61	0.25	0.51
Number of physicians per 10, 000 population	0.36	0.23	0.14	0.82	0.96

Lastly, comparing the BRI results with the SoVI for the five municipalities highlights differences in resilience and vulnerability (Table 3). San German, for example, is more vulnerable than all remaining municipalities except Mayaguez, while being at the same time the most resilient. Mayaguez, on the other hand, was found to be both highly vulnerable and the least resilient.

Table A.4. Social Vulnerability Index (SoVI) and Baseline Resilience Index (BRI) for five municipalities in West PR.

	Anasco	**Hormigueros**	**Mayaguez**	**Rincon**	**San German**
SoVI (0-1)	0.35	0.26	0.75	0.16	0.52
BRI (0-5)	1.47	1.78	1.41	2	2.09

Discussion

One of the major assumptions of this approach is that all variables have equal weight in contributing to resilience, as determining weights for each variable is difficult at this scale and with lacking evidence, and highly prohibiting with 36 variables. However, subjective methods can be leveraged to engage with communities, stakeholders, and decision-makers to assign relative weights (e.g., Bozza, Asprone, & Manfredi, 2015; Etsy et al., 2005). It should also be noted that the BRI represents the resilience of municipalities relative to each other, and not as an objective measure of the overall resilience of each community.

Alternatively to the BRI, the methodology for the SoVI uses ranking and percentiles to normalize each the variables, which are then added together and scaled. While this methodology also treats the variables as equally weighted, using a Min-Max rescaling only helps preserve the distribution and variance of each variable that is lost in rank-percentile calculations. Additionally, the BRI constructed here used American Community Survey 2017 (ACS) 5-year estimates instead of Census 2000 data. The ACS 2017 coincides with the year of Hurricane Maria, relevant to the context of this case study. While ACS estimates are less accurate than decennial data, the 5-year estimates are more reliable than the one and 2-year ACS estimates, and generally appropriate for this level of analysis.

For the social and economic resilience categories, data relied almost entirely on Census data readily found in the American FactFinder database, while the other categories use a wider variety of data sources. As mentioned previously, some data sources do not offer data for PR, which may be due to its commonwealth status as a territory so that it is not counted as part of nationwide databases. To cope with this, alternative data may be pursued as proxies to complete the BRI for PR.

APPENDIX B

INSTITUTIONAL REVIEW BOARD STATEMENT

In compliance with federal regulations on research involving human subjects, data collection processes and analysis were reviewed and exempt by the New York University Institutional Review Board (NYU WSQ) prior initiation of the project (Ref#: IRB-FY2019-2665).