A Validation of Metrics for Community Resilience to Natural Hazards and Disasters Using the Recovery from Hurricane Katrina as a Case Study

Christopher G. Burton

GEM Foundation, Pavia, Italy

How communities respond to and recover from damaging hazard events could be contextualized in terms of their disaster resilience. Although numerous efforts have sought to explain the determinants of disaster resilience, the ability to measure the concept is increasingly being seen as a key step toward disaster risk reduction. The development of standards that are meaningful for measuring resilience remains a challenge, however. This is partially because there are few explicit sets of procedures within the literature that outline how to measure and compare communities in terms of their resilience. The primary purpose of this article is to advance the understanding of the multidimensional nature of disaster resilience and to provide an externally validated set of metrics for measuring resilience at subcounty levels of geography. A set of metrics covering social, economic, institutional, infrastructural, community-based, and environmental dimensions of resilience was identified, and the validity of the metrics is addressed via real-world application using Hurricane Katrina and the recovery of the Mississippi Gulf Coast in the United States as a case study. *Key Words: composite indicators, Hurricane Katrina, recovery, resilience, resilience measurement.*

社群如何回应毁坏性的危害事件、并从中復原，可从其灾害恢復力的角度进行脉络化。儘管已有诸多尝试致力于解释灾害恢復力的决定因素， 但衡量此一概念的能力， 却逐渐被视为降低灾害风险的主要步骤。发展衡量恢復力的标准虽具有意义，却仍然是个挑战，部分原因在于概述如何衡量和比较社群恢復力的文献中，显少提出明确的程序组合。本文的主要目的，便是促进对于灾害恢復力的多重面向本质之理解，并提供经由外部确认的有效度量组，用以衡量地理上郡县次层级的恢復力。本文定义一组涵盖恢復力的社会、经济、制度、基础设施、根据社群以及环境面向的度量组，并以卡翠娜飓风和美国密西西比州湾岸的復原作为案例研究，透过真实世界的应用来处理该度量的有效性。 *关键词： 综合指标，卡翠娜飓风，復原，恢復力，恢復力衡量。*

La manera como las comunidades responden y se recuperan de los efectos devastadores de catástrofes podría contextualizarse en términos de su resiliencia al desastre. Si bien han sido numerosos los intentos por explicar los determinantes de resiliencia al desastre, la capacidad de medir el concepto crecientemente se la identifica como el paso clave hacia la reducción del riesgo en esos eventos. No obstante, el desarrollo de estándares que en verdad sirvan para medir la resiliencia todavía permanece como reto. En parte esto se debe a la escasez de conjuntos de procedimientos disponibles en la literatura que puntualicen cómo medir y comparar las comunidades en términos de su resiliencia. El propósito primario de este artículo es ampliar la comprensión de la naturaleza multidimensional de la resiliencia al desastre y proveer un conjunto de medidas validadas externamente para cuantificar la resiliencia en geografía a niveles de sub-condado. Se identificó un conjunto de medidas que cubren las dimensiones económicas, institucionales, infraestructurales de base comunitaria y las dimensiones ambientales de la resiliencia, al tiempo que la validez de las medidas se aboca vía una aplicación al mundo real, utilizando como estudio de caso al Huracán Katrina y la recuperación de la Costa del Golfo en Mississippi, Estados Unidos. *Palabras clave: indicadores compuestos, Huracán Katrina, recuperación, resiliencia, medición de la resiliencia.*

No place that people live is immune from natural hazards and disasters, and despite great investments in disaster risk reduction, losses from damaging events are increasingly of monumental proportions. Recent disasters in the United States such as Hurricane Sandy and Hurricane Katrina provide examples of impacts where the economic, environmental, and social ramifications are widespread and long lasting. The impacts suffered from such events transcend geographic boundaries and scales,

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and they adversely affect governments, businesses, transportation, economic sectors, and people. It is these circumstances that have stimulated a great interest in understanding how to manage natural hazard risk and, in recent years, research has focused on the capacity of communities to reduce impacts and to facilitate recovery from damaging events with little or no outside assistance. Great emphasis is being placed on fostering disaster-resilient communities by governments, stakeholders, and researchers because communities that can increase their resilience are in a better position to withstand adversity and to recover more quickly when damaging hazard events occur.

Resilient communities are less vulnerable to hazards and disasters than less resilient communities. For this assumption to be useful, though, knowledge of how resilience is determined and how resilience should be assessed is vital (Klein, Nicholls, and Thomalla 2003; Cutter et al. 2008b). Although numerous research communities have sought to explain the determinants of disaster resilience, the ability to measure resilience is increasingly being identified as a key step toward disaster risk reduction. This is because it would be impossible to identify the priority needs for the enhancement of disaster resilience in communities, to monitor changes, to show that resilience has improved, or to compare the benefits of increasing resilience with the associated costs without some numerical means of assessment (National Academies 2012). Measuring resilience is difficult, however. The latter is partially because there are few explicit sets of metrics and procedures within the existing literature that suggest how resilience should be quantified or how to determine whether communities are becoming more or less resilient in the face of an immanent threat (Bruneau et al. 2003; Cutter, Burton, and Emrich 2010).

The purpose of this article is to provide an externally validated set of metrics that could be considered relevant for measuring disaster resilience at subnational levels of geography. Hurricane Katrina and the recovery of the Mississippi Gulf Coast is used as a case study in which a quantified measure of the spatial and temporal recovery of communities along the coast is used as an external validation metric to allocate a set of indicators that could provide a comparative assessment of disaster resilience. Two questions form the basis of this work:

1. What set of indicators provide the best comparative assessment of disaster resilience among communities?
2. To what extent do these indicators predict a known and measurable outcome, such as disaster recovery?

The article proceeds as follows. The first section begins with a discussion of the concept of resilience to natural hazards and disasters. The second section details the methods through which a parsimonious and representative set of indicators was identified. The third section explains the findings. The final section addresses the utility of the findings and offers recommendations for further research.

Resilience to Natural Hazards and Disasters

Understanding Disaster Resilience

The term *resilience* has been used to describe great strength under adversity and the ability to withstand unfavorable circumstances. Holling (1973) is frequently cited as the first to describe the concept in ecology. He compared resilience with the notion of sustainability, where he defined resilience as "the ability to absorb change and disturbance and still maintain the same relationships that control a system's behavior" (Holling 1973, 30). Timmerman (1981) was probably the first to coin the term within natural hazards and disasters research. Timmerman described resilience as the measure of the capacity of a system, or part of a system, to absorb or recover from a damaging event.

Since the publication of the work of Holling and Timmerman, the concept of resilience has gained acceptance in a variety of fields, and there is no broadly accepted definition of the concept despite more than three decades worth of research (Klein, Nicholls, and Thomalla 2003; Manyena 2006; Cutter et al. 2008b). The natural hazards community has been active in describing resilience as the ability to survive and cope with a disaster with minimum impacts and damage (Berke and Campanella 2006; Cutter et al. 2008b). The latter encompasses the capacity of populations to reduce risk, to avoid losses, and to recover from damaging events with little or no social disruptions (Buckle, Marsh, and Smale 2001; Manyena 2006; Tierney and Bruneau 2007). In geography, the notion of risk reduction and loss avoidance is refined to account for inherent conditions within communities that allow them to absorb impacts and

cope with damaging events. This includes post-event processes that facilitate the ability of communities to reorganize, change, and learn in response to a threat (Cutter et al. 2008b).

The global environmental change community has also been active in conceptualizing resilience by emphasizing human–environment interactions (Janssen et al. 2006; Cutter et al. 2008b). This research domain focuses on the measurement of a system's capacity to absorb disturbances and to reorganize into a fully functioning system following an event. This focus includes an understanding of a system's capacity to return to the state (or multiple states) that existed before a disturbance (Klein, Nicholls, and Thomalla 2003; Adger et al. 2005; Folke 2006). The global environmental change community also incorporates the idea of adaptive capacity with resilience. *Adaptive capacity* is described as the ability to adjust to change, moderate the effects of a disturbance, and cope (I. Burton et al. 2002; Brooks, Adger, and Kelly 2005).

Other perspectives see hazard mitigation and planning as key constructs of resilience. Hazard mitigation and planning programs reduce losses by affecting both the location and design of urban development. Where development in hazardous areas cannot be foregone, effective planning might reduce risk by steering development to the least hazardous sites. Conversely, hazard mitigation programs could modify building and site design so that risk is reduced (Burby et al. 1999). Other perspectives on resilience also involve engineered systems. The resilience of engineered systems is often articulated using four properties of resilient infrastructures—robustness, rapidity, redundancy, and resourcefulness (Bruneau et al. 2003; Tierney and Bruneau 2007).

Disaster Resilience Linked to Recovery

This article defines resilience as the ability of social systems to prepare for, respond to, and recover from damaging hazard events (Cutter et al. 2008b). It includes conditions that are inherent and allow communities to absorb impacts and cope with an event. Resilience also encompasses post-event processes that allow communities to reorganize, change, and learn in response to an event (Cutter et al. 2008b). Thus, enhancing a community's resilience to natural hazards is to improve its capacity to anticipate threats, to reduce its overall vulnerability, and to allow the community to recover from adverse impacts when they occur. Decades of hazards and disasters research have offered extensive findings within this context (see Haas, Kates, and Bowden 1977; I. Burton, Kates, and White 1993; Mileti 1999; Kates et al. 2006).

A review of the limited long-term case studies after a disaster shows that recovery from a damaging event takes an extensive amount of time, often measured in years (Kates et al. 2006). Four identifiable postdisaster periods have been identified in this regard: (1) an emergency period that is characterized by search and rescue, sheltering, and the clearing of major arteries; (2) restoration, during which repairable essentials of urban life such as utilities are restored; (3) reconstruction, during which infrastructure and housing is provided for; and (4) a commemorative or betterment reconstruction phase. The time needed for recovery following a disaster could be a multiple of approximately 100 times the extent of the emergency period (I. Burton, Kates, and White 1993; Kates et al. 2006), and there is evidence that recovery processes are closely coupled with preexisting demographic, economic, social, and political trends that lead to very different recovery trajectories among communities (Kates et al. 2006; Cutter et al. 2008b). It is within this context that the fostering of resilient communities can improve recovery outcomes (Bruneau et al. 2003; Tierney and Bruneau 2007; Colten, Kates, and Laska 2008).

This article focuses explicitly on preexisting conditions within communities that could affect hazard impacts and a community's ability to recover following a damaging event. It adopts the inherent resilience portion of the disaster resilience of place (DROP) model for its theoretical basis (see Cutter et al. 2008b) as a result. The starting point of the DROP model begins with a community's antecedent conditions, the product of processes that occur within and between natural systems, the built environment, and social systems at specific places. Antecedent conditions include what Cutter et al. (2008b) referred to as inherent vulnerability and inherent resilience. Inherent vulnerability and inherent resilience provide the focal point for the framework because they are preexisting and measurable characteristics within communities that serve as a baseline set of circumstances from which the effectiveness of programs, polices, and interventions designed to improve disaster resilience can be measured. Social, economic, infrastructural, institutional, community, and environmental components determine the antecedent conditions portion of the DROP model. Each of these components may be

associated with metrics aimed at measuring resilience. The environmental component provides one example because measures of high biodiversity, low erosion rates, and the number of coastal defense structures in a community could affect hazard impact potential, recovery times, and recovery outcomes.

Study Area

This research was accomplished within the context of a particular place. The work focuses explicitly on the Mississippi coastal counties (Hancock, Harrison, and Jackson) largely due to the devastation these areas suffered from storm surge, flooding, and the intense winds from Hurricane Katrina (Figure 1). Prior to the storm, population estimates revealed that nearly 343,000 people resided within the study area (U.S. Census Bureau 2000). Most residents were located in low-lying areas within Harrison and Jackson counties (Knabb, Rhome, and Brown 2005). Due to topography, bathymetry, and human–environment interactions, these residents were particularly vulnerable to catastrophic winds, surges, and flooding from the event.

The analysis for this research was conducted at the census block group resolution, as defined by the U.S. Census Bureau. Census block groups were chosen because they are intended to be fairly stable in population size and are intended to be homogeneous in terms of population characteristics, economic status, and living conditions (Sampson, Morenoff, and Gannon-Rowley 2002). Census block groups also provide a relevant proxy for neighborhoods within urban areas. An alternative approach would have been to focus on data at finer resolutions such as the census block, parcel, or household level. Important socioeconomic data are often not available beyond the census block group resolution level, however. Moreover, the data are less reliable due to techniques used by the U.S. Census Bureau to maintain the confidentiality of information (C. G. Burton 2010).

Methodology

One method to assess characteristics that affect the resilience of communities is through the construction and application of composite indicators. An indicator is a quantitative or qualitative measure derived from observed facts that simplify and communicate the reality of a complex situation (Freudenberg 2003). The mathematical combination (i.e., aggregation) of a set of indicators forms a composite index. The application of composite indicators is not new to research fields requiring empirical measurement, and the scientific literature outlines methodological approaches for index construction (see Freudenberg 2003; Nardo

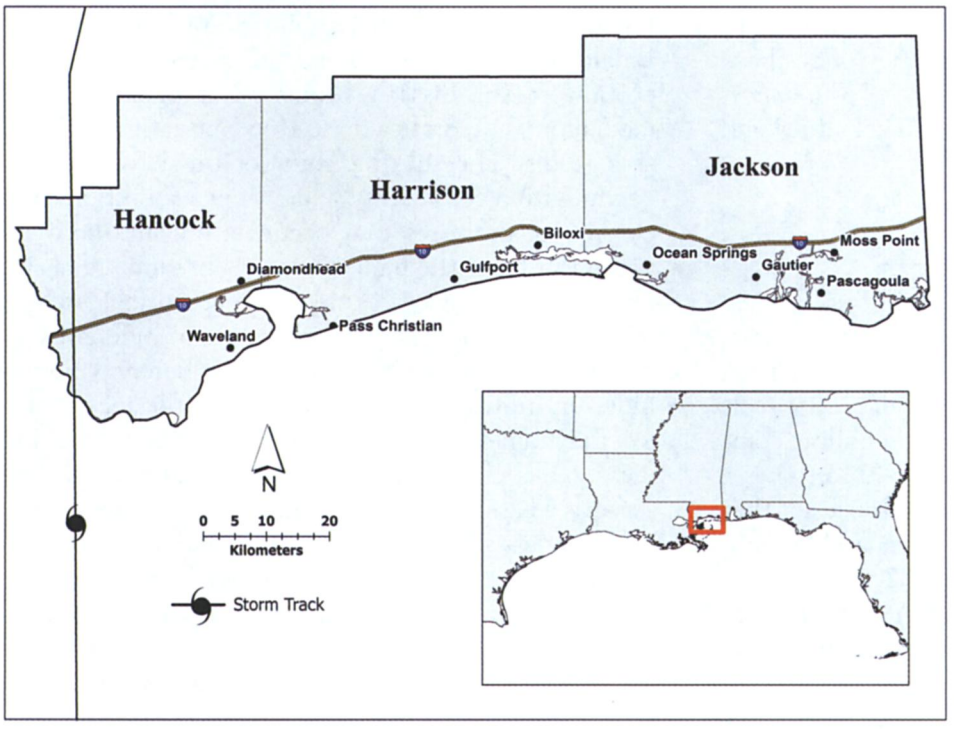

Figure 1. Study area. (Color figure available online.)

et al. 2008; Tate 2012). Most of the literature highlights a number of steps that include (1) the identification of relevant variables, (2) multivariate analyses, (3) aggregation, and (4) linking variables to an external validation metric. The application of these steps to this research is described in the sections that follow.

Components of Disaster Resilience

Because it is difficult to measure resilience in relative terms (Schneiderbauer and Ehrlich 2006; Cutter et al. 2008b; Cutter, Burton, and Emrich 2010), variables were collected as proxy measures to represent the concept within social, economic, infrastructural, institutional, community, and environmental subcomponents. As an initial step, a wish list of approximately 130 variables was compiled and was based on three equally important criteria. First, variables were justified based on the disaster resilience literature and the variable's relevance to one or more of the six categories selected. The second criterion was that variables must be of consistent quality and from publicly available data sources. The third criterion was that variables must be scalable or available at multiple levels of geography. Out of the 130 variables on the wish list, 98 were collected based on the three overarching criteria (Table 1).

The first subcomponent, social resilience, captures social capacities within communities in addition to community health and well-being and equity. The linking of the demographic attributes of communities with social capacities suggests that communities with lower levels of minority residents, fewer elderly, fewer people with disabilities, and fewer people speaking English as a second language likely exhibit greater resilience than communities without these characteristics (Cutter, Burton, and Emrich 2010). Key dimensions of community health and well-being include proxies for psychosocial support access, health service access, child care, adult education and training, social assistance, and access to recreational facilities. The premise is that communities that provide their citizenry with support for health and well-being will constitute a higher standard of living that might affect predisaster impacts and postdisaster recovery processes.

Economic resilience is the second subcomponent and was designed to measure a community's economic and livelihood stabilities, resource diversity, resource equity, and the exposure of a community's economic assets. Key economic and livelihood stability indicators include homeownership, employment status, and the sales volume of businesses. Proxies for resource equity include measures of homeownership disparity, access to lending institutions, and access to physicians and other medical professionals. Economic diversity is measured using proxies that relate to employment type and the ratio of large to small businesses, whereas economic asset exposure is measured with proxies that include the number of commercial establishments in an area.

The institutional resilience component covers hazard mitigation, planning, disaster preparedness, and rapid urban development. Variables were selected to identify the capacity of communities to reduce risk, to engage residents in hazard mitigation activities, and to enhance and protect the social systems on which communities depend. Proxy variables include the measurement of population covered by hazard mitigation and planning initiatives, insurance coverage, and growth management.

The fourth subcomponent, infrastructure resilience, is an evaluation of community response and recovery capacity. Response capacity is defined by variables that include the number of police, fire, emergency relief services, and temporary shelters per population. An appraisal of road and railway infrastructures was also included to evaluate pre-event evacuation capabilities and redundancies within supply routes for postdisaster response and recovery. The infrastructure resilience component also provides an appraisal of the amount of property that could be particularly vulnerable to catastrophic damage and economic loss.

Community capital is the fifth subcomponent. The community capital subcomponent was designed to capture relationships that exist between individuals and their larger neighborhood and community. Community capital directly relates to social capital, a concept that is defined within the context of this article as a set of adaptive capacities that can support the process of community resilience to maintain and sustain community health (Norris et al. 2008; Sherrieb, Norris, and Galea 2010). Here, the primary elements of social capital are (1) social participation, which encompasses places for social interaction to occur; (2) community bonds or a sense of place that is often established through the longevity of residents residing within a community; and (3) innovation.

The environment subcomponent makes up the final component for which variables were collected. This subcomponent is concerned with measures of risk and exposure, the presence of protective resources that

Table 1. Potential indicators for resilience assessment

Type	Variable	Justification
Social resilience		
Social capacity	% population that is not elderly	Cutter, Burton, and Emrich (2010)
	% population with vehicle access	Cutter, Burton, and Emrich (2010)
	% population with telephone access	Cutter, Burton, and Emrich (2010)
	% population that doesn't speak English as a second language	Cutter, Burton, and Emrich (2010)
	% population without a disability	Cutter, Burton, and Emrich (2010)
	% population that is not institutionalized or infirmed	U.S. Indian Ocean Tsunami Warning System Program (2007)
	% population that is not a minority	Tobin (1999)
	% population with at least a high school diploma	Cumming et al. (2005)
	% population living in high-intensity urban areas	Geis and Kutzmark (1995)
Community health/ well-being	Social assistance programs per 1,000 population	U.S. Indian Ocean Tsunami Warning System Program (2007)
	Adult education and training programs per 1,000 population	U.S. Indian Ocean Tsunami Warning System Program (2007)
	Child care programs per 1,000 population	H. John Heinz III Center (2002)
	Community services (recreational facilities, parks, historic sites, libraries, museums) per 1,000 population	Lochner, Kawachia, and Kennedy 1999
	Internet, television, radio, and telecommunications broadcasters per 1,000 population	Aguirre et al. (2005)
	Psychosocial support facilities per 1,000 population	Few (2007)
	Health services per 1,000 population	Lochner, Kawachia, and Kennedy (1999)
Equity	Ratio % college degree to % no high school diploma	Cutter, Burton, and Emrich (2010)
	Ratio % minority to % nonminority population	Tobin (1999)
Economic resilience		
Economic/livelihood stability	% homeownership	Cutter, Burton, and Emrich (2010)
	% working age population that is employed	Cutter, Burton, and Emrich (2010)
	% female labor force participation	Cutter, Burton, and Emrich (2010)
	Per capita household income	Tobin (1999)
	Mean sales volume of businesses	Rose (2007)
Economic diversity	% population not employed in primary industries	Cutter, Burton, and Emrich (2010)
	Ratio of large to small businesses	Cutter et al. (2008a)
	Retail centers per 1,000 population	U.S. Indian Ocean Tsunami Warning System Program (2007)
	Commercial establishments per 1,000 population	U.S. Indian Ocean Tsunami Warning System Program (2007)
Resource equity	Lending institutions per 1,000 population	Queste and Lauwe (2006)
	Doctors and medical professionals per 1,000 population	Cutter, Burton, and Emrich (2010)
	Ratio % white to % nonwhite homeowners	Cutter, Burton, and Emrich (2010)
Economic infrastructure exposure	% commercial establishments outside of high hazard zones (flood, surge)	U.S. Indian Ocean Tsunami Warning System Program (2007)
	Density of commercial infrastructure	Allenby and Fink (2005)
Institutional resilience		
Hazard mitigation/ planning	% population covered by a recent hazard mitigation plan	Cutter, Burton, and Emrich (2010)
	% population participating in Community Rating System (CRS) for flood	Cutter, Burton, and Emrich (2010)
	% households covered by National Flood Insurance Program policies	Cutter, Burton, and Emrich (2010)
Preparedness	% population with Citizen Corps program participation	Cutter, Burton, and Emrich (2010)
	% workforce employed in emergency services (firefighting, law enforcement, protection)	Cutter et al. (2008b)
	Number of paid disaster declarations	Cutter, Burton, and Emrich (2010)
Development	% land cover change to urban areas from 1990 to 2000	H. John Heinz III Center (2002)

(*continued on next page*)

Table 1. Potential indicators for resilience assessment *(Continued)*

Type	Variable	Justification
Infrastructure resilience		
Housing type	% housing that is not a mobile home	Cutter, Burton, and Emrich (2010)
	% housing not built before 1970; after 1994	Cutter, Burton, and Emrich (2010)
Response and recovery	% housing that is vacant rental units	Cutter, Burton, and Emrich (2010)
	Hotels and motels per square mile	Cutter, Burton, and Emrich (2010)
	Fire, police, emergency relief services, and temporary shelters per 1,000 population	U.S. Indian Ocean Tsunami Warning System Program (2007)
	% fire, police, emergency relief services, and temporary shelters outside of hazard zones	U.S. Indian Ocean Tsunami Warning System Program (2007)
	Schools (primary and secondary education) per square mile	Cutter, Burton, and Emrich (2010)
Access and evacuation	Principal arterial miles	Cutter, Burton, and Emrich (2010)
	Number of rail miles	Cutter et al. (2008a)
Infrastructure exposure	Density of single-family detached homes	Cutter et al. (2008a)
	% building infrastructure not in flood and storm surge inundation zones	Geis and Kutzmark (1995)
	% building infrastructure not in high hazard erosion zones	Geis and Kutzmark (1995)
Community capital		
Social capital	Religious organizations per 1,000 population	Cutter, Burton, and Emrich (2010)
	Social advocacy organizations per 1,000 population	Cutter, Burton, and Emrich (2010)
	Arts, entertainment, and recreation centers per 1,000 population	H. John Heinz III Center (2002)
	Civic organizations per 1,000 population	Cutter, Burton, and Emrich (2010)
Creative class	% workforce employed in professional occupations	Cumming et al. (2005)
	Professional, scientific, and technical services per 1,000 population	Cumming et al. (2005)
	Research and development firms per 1,000 population	Cumming et al. (2005)
	Business and professional organizations per 1,000 population	Lochner, Kawachia, and Kennedy (1999)
Cultural resources	National Historic Registry sites per square mile	U.S. Indian Ocean Tsunami Warning System Program (2007)
Sense of place	% population born in a state and still residing in that state	Cutter, Burton, and Emrich (2010)
	% population that is not an international migrant	Cumming et al. (2005)
Environmental systems resilience		
Risk and exposure	% land area that does not contain erodible soils	Bradley and Grainger (2004)
	% land area not in an inundation zone (100/500-year flood and storm surge combined)	Cutter et al. (2008a)
	% land area not in high landslide incidence zones	Schneiderbauer and Ehrlich (2006)
	Number of river miles	Berke and Campanella (2006)
Sustainability	% land area that is nondeveloped forest	Cutter et al. (2008a)
	% land area with no wetland decline	Cutter et al. (2008b)
	% land area with no land-cover/land-use change, 1992–2001	United Nations Department of Economic and Social Affairs (2007)
	% land area under protected status	U.S. Indian Ocean Tsunami Warning System Program (2007)
	% land area that is arable cultivated land	United Nations Department of Economic and Social Affairs (2007)
Protective resources	% land area that consists of windbreaks and environmental plantings	Cutter et al. (2008b)
	% land area that is a wetland, swamp, marsh, mangrove, sand dune, or natural barrier	Cutter et al. (2008b)
	% land area that is developed open space	Geis and Kutzmark (1995)
Hazard event frequency	Frequency of loss-causing weather events (hail, wind, tornado, hurricane)	Greiving (2006)

buffer communities against environmental threats, and dimensions of sustainability. Variables such as the land area that is not in an inundation zone (flood and storm surge), that does not contain erodible soils, and that is not in landslide incidence zones were incorporated to capture risk and exposure. To account for protective resources that are both natural and anthropogenic, variables were culled to represent land that is nondeveloped open space and the amount of land that consists of windbreaks, wetlands, mangroves, swamps, and marshland. The environmental subcomponent also incorporates sustainability measures that are directly related to the exposure of populations, the prevalence of resources that protect and buffer against damaging impacts, and nondeveloped open space.

Multivariate Analysis

Because there is no definitive set of indicators for measuring disaster resilience, the selection of variables was subjective. The quality of composite indicators and the soundness of the messages they convey depend not only on the methods used in the construction process but also on the internal consistency of the variables selected (i.e., how well the variables might measure the underlying concept). A series of multivariate analyses was conducted to distinguish potentially relevant from nonrelevant data and to reduce the data to a parsimonious set of metrics. As a first step, the raw data were transformed into comparable scales using either percentage, per capita, and density functions where the transformation type was based on how a particular variable was described in the literature or based on the author's expert judgement. The data were then standardized using a Min–Max rescaling scheme to create a set of indicators on the same measurement scale. Min–Max rescaling rescales each variable into an identical range between 0 and 1 (a score of 0 being the worst rank for an indicator score and 1 being the best rank). A ninety-eight by ninety-eight dimension correlation analysis was conducted as a third step using the entirety of the data. Preliminary testing of the data revealed a large number of nonparametric and nonlinear relationships between variables. Thus, a nonlinear and nonparametric correlation analysis was applied to assess the associations between the variables. During the correlation step, twenty-three variables were interpreted as highly correlated (Spearman's $R > 0.700$). All highly correlated variables were eliminated from further consideration to avoid subjectively choosing one variable over another for inclusion in subsequent analyses.

In addition to correlation, a multidimensional scaling (MDS) analysis was conducted for the variables in each subcomponent in isolation. MDS was employed to gauge the internal consistency of the variables in an effort to discriminate relevant data from potentially irrelevant data. MDS is an integral part of multidimensional similarity structure analysis that represents similarity coefficients among data using distances in multidimensional space (Borg and Lingoes 1987). It is a technique that is often considered to be a nonparametric alternative to factor analysis (FA). Given a matrix of variables, the procedure represents the data as points mapped in a Euclidian plane where two points are closer together when variables are similar in terms of their distances. The Euclidean plane of points was evaluated under the assumption that variables spaced closer together might be internally consistent and appropriate for measuring their underlying dimension of resilience. Using this procedure, variables mapped at great distances from clusters of similar data were scrutinized to understand their source for being an outlier and were subsequently omitted from further analysis.

The correlation analysis was useful in reducing the data from $n = 98$ to $n = 75$ variables. The data were reduced further from $n = 75$ to $n = 64$ variables using the MDS procedure. The remaining sixty-four variables were considered internally consistent and appropriate for testing against the Hurricane Katrina disaster recovery phenomenon. The procedure to validate the variables is described in the section that follows.

Field Method for Long-Term Recovery Assessment

A spatiotemporal assessment of the recovery following Hurricane Katrina was used as an external validation metric to identify variables that might be sufficient for use in a disaster resilience index. This article defines recovery as the process of reconstructing communities to return life, livelihoods, and the built environment to their preimpact states (C. G. Burton, Mitchell, and Cutter 2011). Recovery from a damaging event such as Hurricane Katrina depends on a number of factors and could include social and institutional capacities, the financial reserves of individuals and communities, the social cohesion within communities, the severity of damages sustained, and the

proportion of a community adversely affected. The validation metric for this article focuses explicitly on the material manifestation of recovery along the Mississippi coast (i.e., the reconstruction of the built environment) although this work is sensitive to the multifaceted nature of recovery. The rationale for considering the reconstruction of the built environment is that reconstruction is essential for returning life and livelihoods to preimpact levels of functioning.

The field work for the validation portion of this article began in October 2005 as part of a U.S. National Science Foundation (NSF) funded initiative (see C. G. Burton, Mitchell, and Cutter 2011) to better understand sociospatial disparities in disaster recovery from Hurricane Katrina. Roughly six weeks following Katrina's landfall, a baseline to document the recovery process was established using an evenly spaced 1.6 km × 1.6 km grid of points that was generated in a geographic information system (GIS) to cover the entirety of the Mississippi coast. The grid was developed to achieve an evenly spaced sampling strategy for in situ observations of damage impacts and recovery and was placed over a SLOSH (sea, lake, and overland surges from hurricanes) output that was used to represent modeled surge conditions. From the SLOSH output extent, the grid was extended inland for an additional 4.8 km. This procedure generated 1,166 potential sampling points for the study area.

The starting point for the survey process was designated points most assessable and closest to the coast. If storm surge and respective damages to infrastructure were present, the research team moved directly to the point 1.6 km to the north. The process was repeated until no visible cues for storm surge and damages were present. At each point, a photograph was taken in each cardinal direction (N, E, S, and W), and ancillary data were collected that included a subjective measure of the storm's impact severity. On subsequent visits (every six months to date), the research team focused on documenting the spatial and temporal dimensions of the recovery process using repeat photography (rephotographing the same scene as it appears in an earlier photograph). The work employs photographic evidence at 131 different sites (Figure 2) for October 2005, February 2006, October 2006, March 2007, October 2007, March 2008, October 2008, March 2009, October 2009, February 2010, and October 2010. With one photograph for each cardinal direction on ten trips, 5,764 photographs were utilized to document the recovery process.

A comparison of the images from one time period to the next permitted the spatiotemporal representation of the recovery process for the Mississippi coast. The

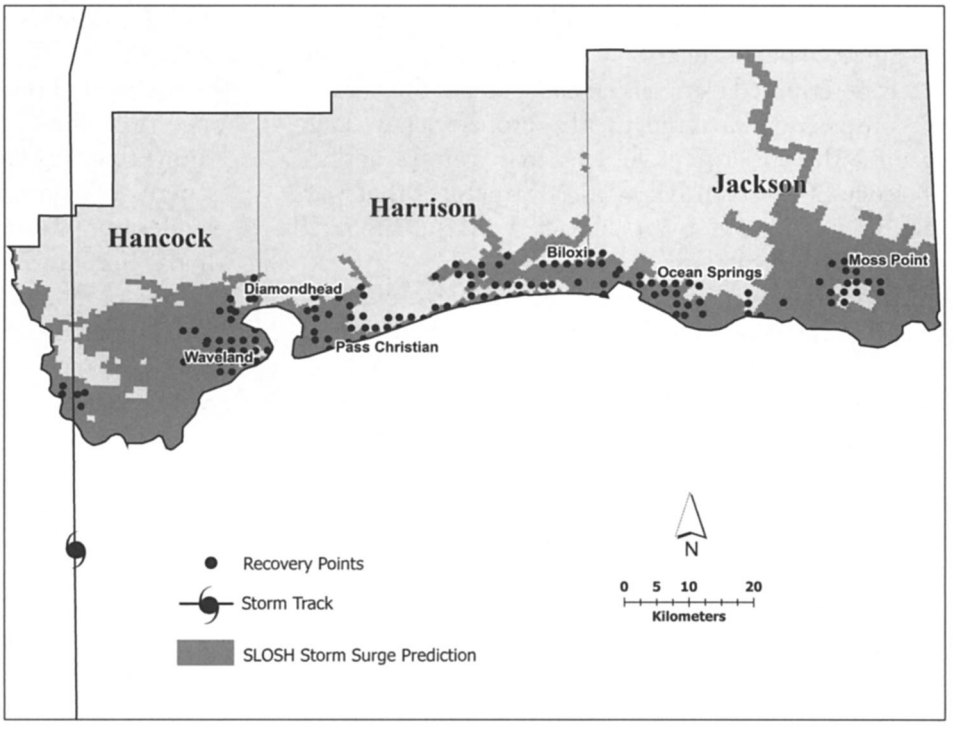

Figure 2. Observation points for photographic evidence of recovery.

Table 2. Recovery and reconstruction categorizations

Category	Description	Score
No recovery/ reconstruction	No visible recovery or reconstruction	0
Stage I recovery	Clean-up: Some or total debris removal	25
Stage II recovery	Demolition, cleared to slab or concrete poured, infrastructure renewal	50
Stage III reconstruction	Rebuilding exterior or interior	75
Full recovery	Full recovery and reconstruction	100

photographic evidence was evaluated to sort the progression of recovery that is occurring into five basic categories (see Table 2). The no recovery/reconstruction category is concerned with a lack of any visible signs of recovery at a point. In Stage I recovery, the clean-up process has begun and is based on the partial or total removal of the debris. Stage II recovery refers to the complete demolition of catastrophically damaged structures as well as the reestablishment of infrastructure that is critical to the reconstruction process, such as power lines, sewer, and water. Visual evidence of Stage II recovery includes the removal of damaged frames and foundations as well as the provision of utilities such as the addition of power lines. In Stage III reconstruction, the rebuilding of the exterior and interior of structures has begun. In the final category, full recovery, the site has been fully reconstructed and occupied. The occupation of structures was subjectively determined using visual cues such as the absence of construction material on the property, new landscaping, the presence of vehicles in driveways, and the presence of personal belongings. Structures that were rebuilt, but vacant, were classified in the Stage III reconstruction category.

Using the primary set of photographs taken in October 2005 as a baseline, each subsequent photograph was evaluated and scores between 0 and 100 were assigned in a GIS database to each respective point. Consistent with the methodology of C. G. Burton, Mitchell, and Cutter (2011), an evaluation received a score of 0 if no visible sign of recovery had occurred. If on a subsequent trip clean-up and debris removal had occurred, the observation received a score of 25, or the observation received a score of 50, 75, or 100 if the progression of recovery in that photo was further along the recovery continuum. Each point was evaluated using photographs in all four cardinal directions to produce a recovery score for each time period at all 131 different observation points. An overall recovery score per point was obtained by averaging the scores in each direction for every time period. Within this context, it is important to acknowledge that recovery from different states of damage will not occur in an identical manner. For instance, the potential is great that a moderately damaged structure will not go through the process of demolition but will proceed directly from hurricane impact to repair. It is therefore possible to obtain a recovery value further along the continuum where appropriate.

Linking Recovery to Disaster Resilience Indicators

To identify variables associated with the recovery process, a multivariate regression modeling procedure was used. A regression analysis was chosen for the comparative portion of this research because regression provides a simplistic view of the relationship between variables. To generate the response variables needed for the regression modeling, the sampling of recovery points and their respective scores were spatially joined to intersecting census block groups. As part of the process of spatially joining the points to the census polygons, a mean recovery score per census block group was generated.

The regression models incorporated the mean recovery scores as response variables and the variables in each of the six subcomponents of disaster resilience ($X1_i$, $X2_i$ ... X_i) as predictor variables. This allowed for the prediction of Y_i (a disaster recovery outcome at one, two, three, four, and five years following the storm) that was based on the variables in the subcomponents of disaster resilience $X1_i$, $X2_i$ ... X_i. For this article, an ordinal logistic regression model (sometimes referred to as a *cumulative logit* model) was used because preliminary testing of the data showed a violation of regression's linearity and normality assumptions. Ordinal logistic regression exists to handle cases where dependent variables have more than two dichotomous classes and where multiple classes of the dependent variable are ordered (i.e., no recovery, Stage I recovery, Stage II recovery, Stage III reconstruction, and full recovery). As opposed to fitting a straight line to the data, a logistic regression applies maximum likelihood estimation after transforming the dependent variable into a logit variable (Fox 2000). A logit variable is the natural log of the odds of a dependent variable equaling a certain value, meaning that the logit model is based on the odds of a certain value

(or event) occurring. In this case, the event occurring is movement from one recovery category to the next over time toward a full recovery.

A total of thirty regression models were calibrated to represent all subindexes individually for the recovery years to assess the association of the proxy variables with the recovery process within their respective categorizations of resilience. In other words, a regression model was calibrated for the variables of each of the six subcomponents for each recovery year. Calibrating a regression model for each year was based on the assumption that block groups would progress from one recovery category to the next and block groups might cluster in certain recovery categories over time. Using a regression model for each year accounts for circumstances in which certain variables might be better associated with specific recovery stages at periods in time due to derived beta coefficients that are sensitive to the distribution of values in the response variables. To prepare the dependent variables for use in an ordinal logistic model, each census block group was nominally coded to differentiate between recovery categories where a value of 1 represents all block groups in Stage I recovery (average scores >25 and <50), 2 represents all block groups in Stage II recovery (average scores ≥ 50 and <75), 3 represents all block groups in Stage III reconstruction (average scores ≥ 75 and <100), and a value of 4 represents all block groups that have fully recovered (average scores = 100). The no recovery categorization was not used because all study area block groups exhibited some form of reconstruction, and their average recovery scores were ≥ 25.

Results

A visual inspection of the response variables in Figures 3 through 5 shows a spatially variable recovery process over time. Only the results for one, three, and five years following Hurricane Katrina are reported here due to space constraints. The darker shades of red represent a limited or punctuated progression of recovery along the coast. One year following the storm (Figure 3), a limited recovery occurred in most communities closest to Hurricane Katrina's storm track and directly adjacent to the coastline. These communities include Waveland, Pass Christian, and a portion of the Diamondhead community that is south of U.S. Interstate 10. Here, storm surge elevations generally exceeded twenty-three feet (Knabb, Rhome, and Brown 2005) and left little more than the foundations on which homes, businesses, government buildings, and churches once stood.

A differential recovery within and between communities is also evident in subsequent years (Figures 4 and 5). Of interest are communities

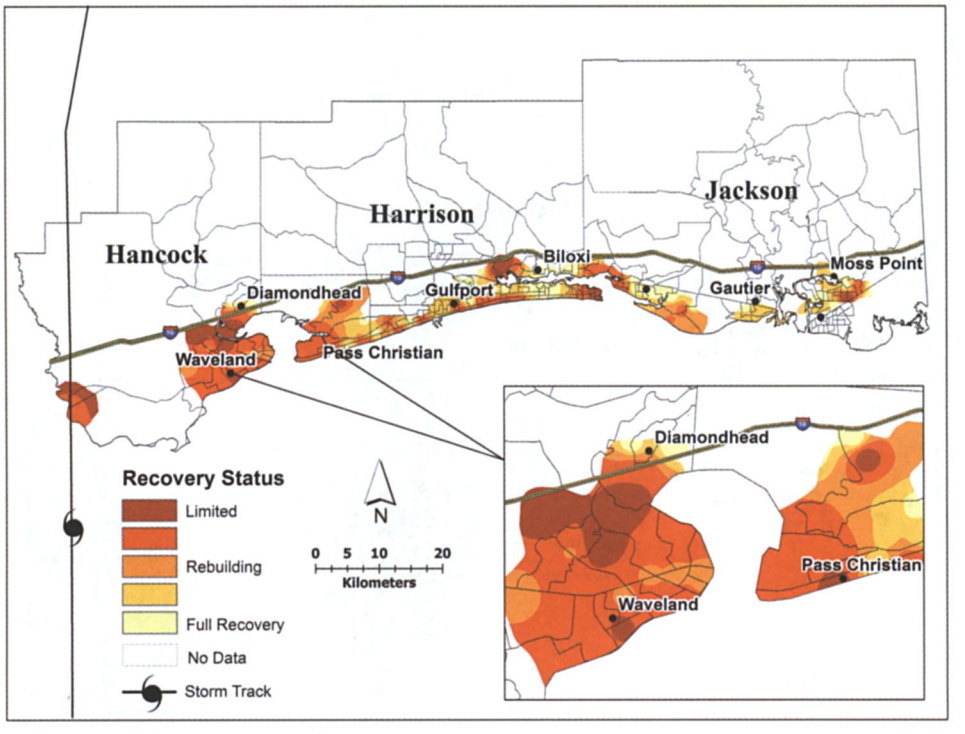

Figure 3. Recovery status for October 2005–October 2006. (Color figure available online.)

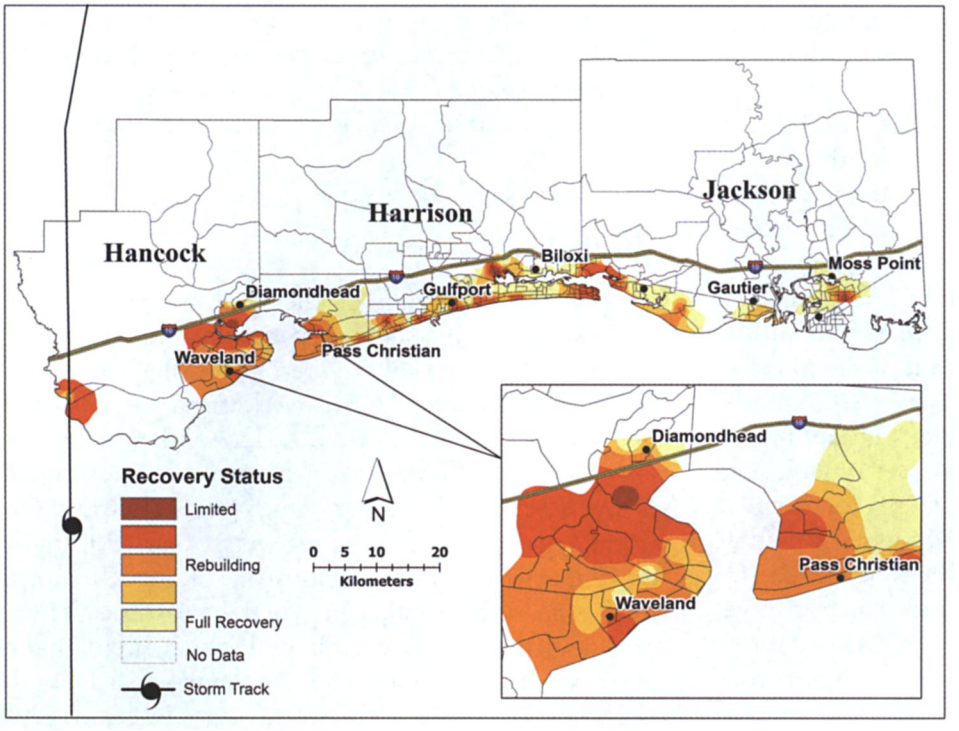

Figure 4. Recovery status for October 2007–October 2008. (Color figure available online.)

directly adjacent to the coast that suffered storm surge inundations and damages similar to those in Waveland and Pass Christian but are closer to a full recovery status than those cities. Also of interest is the differential progression of recovery that is occurring among the communities of Waveland, Pass Christian, and Diamondhead because these communities are in close proximity and suffered similar

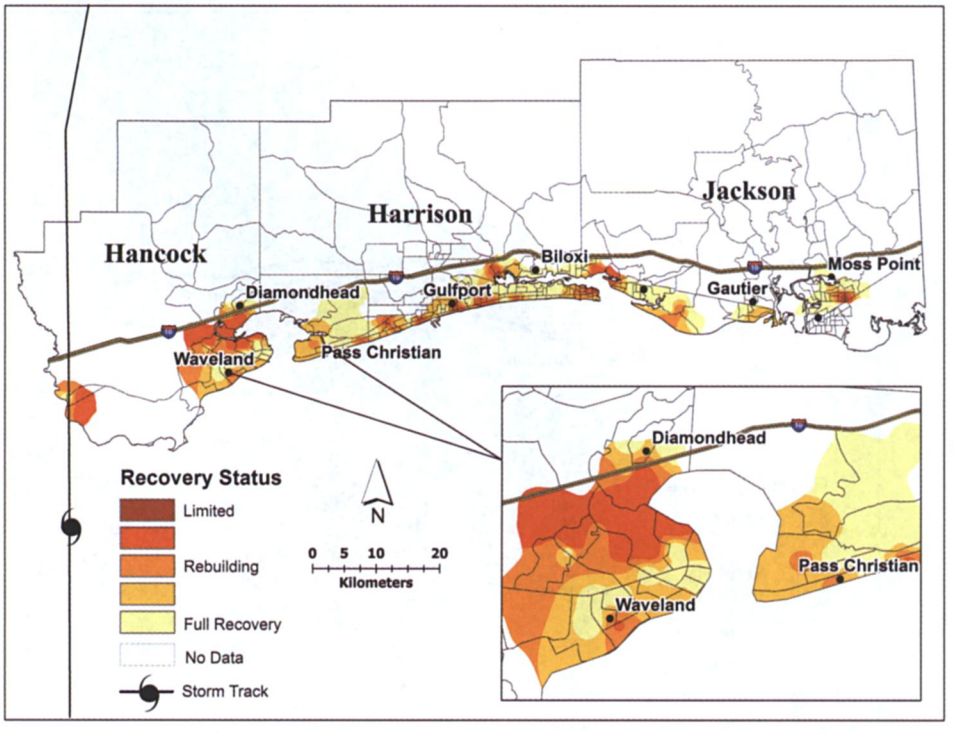

Figure 5. Recovery status for October 2009–October 2010. (Color figure available online.)

impacts. It is spatial differentiations like these that provide the basis for the regression analyses.

The regression analyses to select a set of indicators that could provide a comparative assessment of disaster resilience among communities revealed that forty-one out of the sixty-four indicators might be fit for measuring disaster resilience (Table 3). The decision on fitness for purpose was based on statistical significance ($p \leq 0.050$). All regression models were used to cull statistically significant variables. Only the statistical results for one, three, and five years following the storm are displayed, however, due to the large size of the output tables. All statistically significant variables are contained therein.

The parameter estimates denoted by B relate the recovery of the Mississippi Gulf Coast to the parameters selected to measure resilience. The order of the importance of the variables is highlighted by their regression coefficients that are sorted in descending order from the fifth year of recovery. The R^2 statistics for the models range from 0.022 to 0.224. The explanatory power is low, yet it should be recognized that each subcomponent comprises one sixth of the subcomponents proposed to measure resilience. At this juncture, it was hypothesized that the mathematical combination of the social, economic, institutional, infrastructure, community, and environmental subcomponents would constitute an increase in explanatory power when applied to the recovery outcomes as a whole.

The results of the models for the social component suggest that the percentage of the population that is not a minority and the percentage of the population that has at least a high school diploma are the strongest predictors. Of all of the variables within the subcomponent, the percentage of the population that is a nonminority is the strongest predictor of recovery for the five-year period. This finding is noteworthy because membership in a racial or ethnic minority group directly relates to social and economic marginalization (Cutter, Boruff, and Shirley 2003) that affects natural hazard impacts and recovery.

In the economic resilience subcomponent, per capita income and the percentage of the population that are homeowners are predictors of the recovery process. The extent to which populations have sufficient assets and financial resources to respond to disruptions is a core factor that makes up the resilience of communities. When large segments of a community are poor, it is less plausible to expect residents to be able to anticipate and respond to natural hazard events because it is unlikely that communities will have funds available for emergency preparation, resources to assist residents during the recovery process, or the ability to provide impact and recovery services (Morrow 2008). The per capita income variable is not statistically significant beyond the first year of recovery, however. This could be attributed to circumstances where communities having the economic vitality to recover did so quickly, whereas differential social capacities to respond to the event became a factor affecting the recovery outcome in the long term.

Within the institutional resilience subcomponent, both the presence of a hazard mitigation plan and the National Flood Insurance Program (NFIP) variable were predictors of recovery. Both proxies fall under the scope of nonstructural hazard mitigation and planning initiatives. Berke and Campanella (2006) outlined core reasons why hazard mitigation and planning are essential for building resilience within communities. First, hazard mitigation and planning offers a vision for the future and a means to reduce disaster loss and to promote recovery from damaging events. Community participation in the NFIP, where communities as a whole practice flood mitigation to manage floodplain development and to reduce potential flood losses, provides an example (Federal Emergency Management Agency 2011).

Predictors for infrastructure resilience include housing density, nonmobile homes, and the primary and secondary schools variable. Housing density and the prevalence of structures that are not mobile homes directly relate to the number and type of structures in harm's way (Cutter, Boruff, and Shirley 2003). Primary and secondary schools are vital to a community's recovery process because they can be used for temporary sheltering and provide incentive for dislocated families to return following a damaging event (Ronan and Johnston 2005). Moreover, schools provide important links among children, families, and the wider community in preparing for and responding to disaster events (Johnston et al. 2011).

In the community capital subcomponent the presence of (1) art, entertainment, and recreation centers; (2) religious organizations; (3) social advocacy organizations; and (4) professional service occupations were found statistically significant by the regression models. Here, the ability to recover is a function of innovation, community involvement, and personal community support. Religious organizations and social advocacy organizations are also key drivers of recovery in terms of postevent personal support and involvement.

Table 3. Regression results of potential variables

	B October 2006	B October 2008	B October 2010
Social resilience			
% population that is not a minority	0.719***	1.620*	0.626*
% population that doesn't speak English as a second language	0.420*	0.221*	0.600*
% population with at least a high school diploma	0.654**	0.593**	0.347**
Social assistance programs per 1,000 population	0.424*	0.427*	0.346**
% population with vehicle access	*ns*	0.274*	0.297*
% population with telephone access	0.163*	0.242*	0.144*
Community services (recreational facilities, parks, historic sites, libraries, museums) per 1,000 population	0.193*	0.360*	*ns*
% population without a disability	0.114***	0.218**	*ns*
Health services per 1,000 population	*ns*	0.108*	*ns*
Adult education and training programs per 1,000 population	0.169*	*ns*	*ns*
Economic resilience			
% homeownership	2.053**	1.053***	1.209**
Doctors and medical professionals per 1,000 population	0.147*	0.320*	0.851*
Lending institutions per 1,000 population	*ns*	*ns*	0.585*
Mean sales volume of businesses	0.894**	*ns*	0.432*
% working-age population that is employed	1.137**	0.978**	0.395**
Commercial establishments per 1,000 population	*ns*	*ns*	0.132***
% population not employed in primary industries	*ns*	0.365*	*ns*
Ratio of large to small businesses	0.703*	0.317*	*ns*
% female labor force participation	0.313*	*ns*	*ns*
Per-capita household income	2.891**	*ns*	*ns*
Institutional resilience			
% population participating in Community Rating System (CRS) for flood	0.322*	0.569*	0.682*
% population covered by a recent hazard mitigation plan	0.553*	0.375*	0.337*
% households covered by National Flood Insurance Program policies	0.306*	0.334*	*ns*
% population with Citizen Corps program participation	0.066	*ns*	*ns*
Infrastructure resilience			
Schools (primary and secondary education) per square mile	0.876*	0.822*	0.692**
Principal arterial miles	0.195*	0.111*	0.233*
% housing that is not a mobile home	0.379*	*ns*	*ns*
Fire, police, emergency relief services, and temporary shelters per 1,000 population	0.043***	*ns*	*ns*
% fire, police, emergency relief services, and temporary shelters outside of hazard zones	0.022*	*ns*	*ns*
Density of single-family detached homes	–1.025*	–0.738*	–0.693*
Community capital			
Professional, scientific, and technical services per 1,000 population	0.103*	0.911*	1.301*
Social advocacy organizations per 1,000 population	0.826*	0.621*	0.923*
Arts, entertainment, and recreation centers per 1,000 population	0.298*	0.162*	0.114*
Religious organizations per 1,000 population	1.345*	*ns*	*ns*
Environmental resilience			
% land area with no wetland decline	0.855***	0.530**	0.572*
Frequency of loss-causing weather events (hail, wind, tornado, hurricane)	*ns*	0.897*	0.519*
% land area with no land-cover/land-use change, 1992–2001	1.003*	0.887*	*ns*
% land area that is a wetland, swamp, marsh, mangrove, sand dune, or natural barrier	1.311	*ns*	*ns*
% land area under protected status	0.796*	*ns*	*ns*
% land area that is nondeveloped forest	0.138*	*ns*	*ns*
Number of river miles	–0.178*	*ns*	–0.224*

Note: For all models, significance ≤ 0.05; pseudo $R^2 = 0.022$ to 0.224 (Nagelkerke).
*Significant at 0.05.
**Significant at 0.01.
***Significant at 0.001.

Religious organizations provide linkages among people, family networks, friends, and acquaintances to support and sustain disaster resilience (Buckle 2006). Social advocacy organizations provide pre- and post-event support to communities through outreach services, community development, community advocacy, and the capacity to support appropriate resilience generating activities.

Within the environmental component, the percentage of land area that is swamp, marshland, wetland, and dunes; the percentage of land area with no wetland decline; and the percentage of land area with no land-use/land-cover change showed predictive strength. These variables not only represent the sustainability of biodiversity within natural systems but they also offer a measure of the ability of natural systems to provide protection and to absorb impacts during an event (Eakin and Luers 2006). Changes within these proxies over time are often due to economic development pressures, population growth, and changes in economic and demographic conditions that might set the stage for more frequent and severe disasters that are difficult to recover from.

Mapping the Disaster Resilience of the Mississippi Coast

Up until this point, this article has been concerned exclusively with the identification of a validated set of variables for measuring disaster resilience. To display the relative resilience of the Mississippi coast, a disaster resilience index was developed using the variables identified as being statistically associated with the recovery process (see Table 3). The method of aggregation to derive a final resilience score is the summation of equally weighted average subcomponent scores (Cutter, Burton, and Emrich 2010). In other words, the variable scores for each subcomponent of resilience (social, economic, institutional, infrastructure, community, environmental) were averaged to reduce the influence of a differential number of variables within each subcomponent contributing unevenly to the subcomponent's output score. Each subcomponent score was then summed to derive a final composite score of disaster resilience. Because there are six subcomponents, the summed score of the composite index ranges between 0 and 6 (0 being the least and 6 being the most resilient). A hierarchical modeling approach using subindexes was chosen because the method of aggregation is easy to understand and allows the separate dimensions of resilience to be mapped and analyzed in a manner that is straightforward. Equal weights were chosen because there was no theoretical or practical justification for the allocation of importance across indicators for this particular case study.

The aggregated index scores provide a comparative assessment of the resilience of the Mississippi Gulf Coast (Figure 6). The scores are mapped as standard

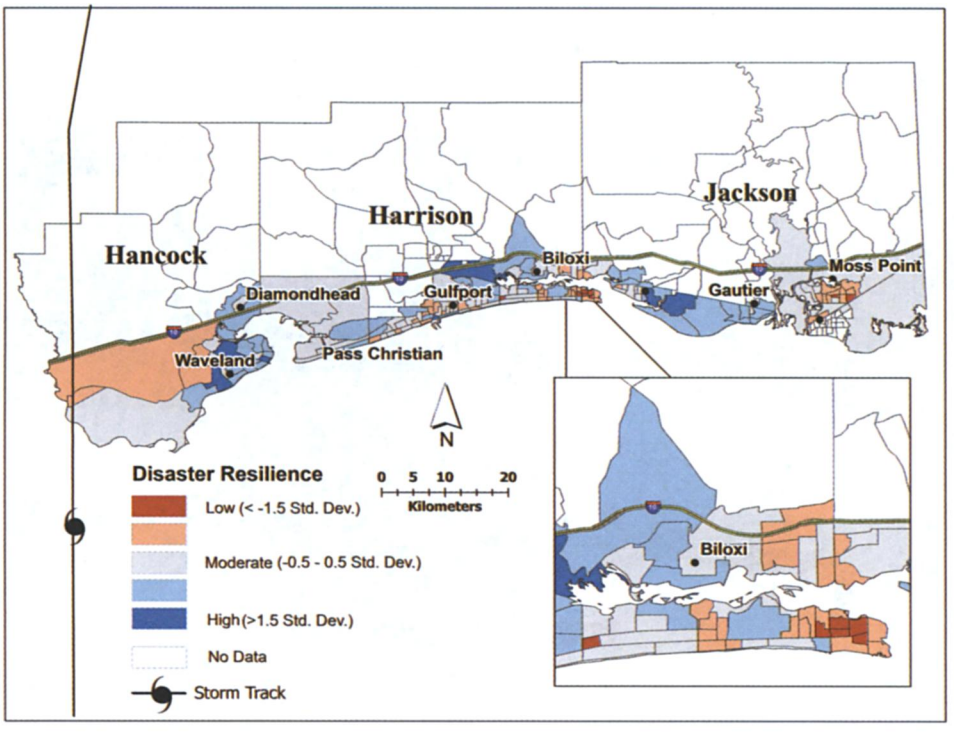

Figure 6. Spatial distribution of disaster resilience. (Color figure available online.)

deviations from the mean to highlight those census block groups that rank exceptionally well or exceptionally poor in terms of their resilience. The block groups symbolized in dark blue are the most resilient. The block groups symbolized in dark red are the least resilient. When mapped, the geographic variations in the resilience of communities become evident. Some of the block groups closest to Hurricane Katrina's storm track, which suffered severe damage (e.g., the communities of Waveland and Diamondhead), have the highest levels of resilience. Ocean Springs, a community situated in western Hancock County, is also composed of block groups with high levels of disaster resilience. Eastern Biloxi and portions of the city of Moss Point are notable due to their low resilience, as pointed out within the inset map.

To visually address some of the underlying factors that contribute to these trends, the composite social, economic, institutional, infrastructure, community, and environmental components of the resilience index are mapped in Figure 7. Several patterns are noteworthy. First, block groups with the highest social resilience (Figure 7A) tend to cluster closest to the coast in affluent and middle-class communities such as Diamondhead and Ocean Springs. The lowest levels of social resilience are found in portions of Gulfport City as well as in East Biloxi and Moss Point, where recovery has been most differential. The social resilience of Gulfport is notable, being that the total disaster resilience of the city is high, comparatively. In Figure 7B, the spatial distribution of the economic subcomponent follows a similar pattern as the social component where lower levels of economic resilience are clustered in East Biloxi, Moss Point, and Gulfport. Conversely, high levels of economic resilience cluster in Diamondhead, Ocean Springs, and portions of Waveland. The institutional resilience subcomponent (Figure 7C) demonstrates low levels of institutional resilience overall with the exception of portions of Waveland, Diamondhead (south of Interstate 10), and block groups in Ocean Springs, Biloxi, and Pass Christian. Infrastructure resilience (Figure 7D) is high in Diamondhead and Ocean Springs, and the community capital subcomponent (Figure 7E) shows the highest levels of resilience directly adjacent to the coast and in eastern Ocean Springs. The environmental subcomponent shows the highest levels of resilience in the southern portions of Hancock and Jackson Counties (Figure 7F) where population and infrastructure densities are lower than those in Harrison County. The spatial variation found among these subcomponents demonstrates the multidimensional nature of the concept as well as the utility of mapping resilience at the subcomponent level for disaster impact and risk reduction.

The Contribution of Resilience Factors to Recovery

When visualized in the form of composite maps of resilience, the geographic variation in the factors

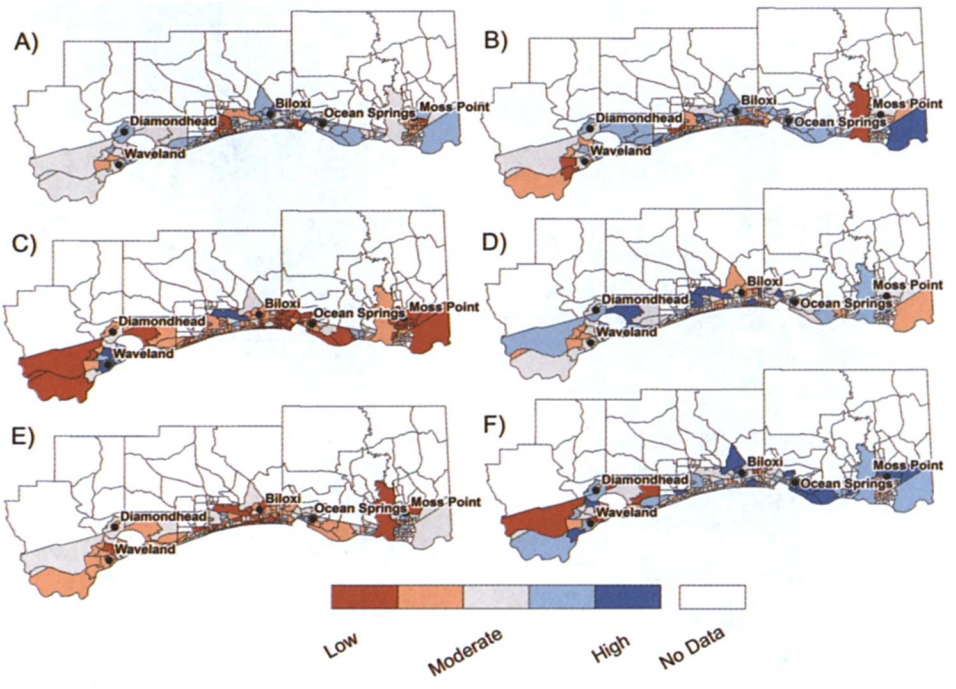

Figure 7. Resilience subcomponents: (A) Social, (B) Economic, (C) Institutional, (D) Infrastructure, (E) Community capital, (F) Environmental. (Color figure available online.)

associated with the recovery of the Mississippi Gulf Coast varies across space. These findings, along with the regression results, illustrate that the widespread impacts and recovery from Hurricane Katrina are not random but manifested from a set of interacting conditions. To better understand the extent of the contribution of the resilience indicators to the recovery outcome along the coast, a binary logistic regression model was calibrated to relate those block groups that have fully recovered (or not fully recovered) by the fifth year to the six aggregated subcomponents of disaster resilience. The regression model was extended to account for damage based on U.S. National Geospatial-Intelligence Agency (NGA) Hurricane Katrina damage assessment layers that were used to estimate the percentage of structures damaged per block group (moderate to catastrophic). This methodology is discussed elsewhere (C. G. Burton 2012).

To prepare the response variable for use in the regression analysis, the average block group recovery scores were nominally coded to differentiate between recovery where a value of 1 was assigned to block groups that have achieved a full recovery (average scores = 100) and a value of 0 was assigned to block groups that have not achieved a full recovery (average score <100). The parameter estimates in Table 4 relate the study area's recovery to the damage and resilience subcomponents. All model parameters achieved a statistical significance ≤ 0.050. The explanatory power of the model is $R^2 = 0.282$. The explanatory power is low to moderately low for the five-year period, which suggests that contextual factors not measured here are contributing substantially to the recovery process over time. These factors might include the extent of social networking within and between communities, the distribution of federal disaster relief aid, local disaster funding priorities, and local decision-making processes.

Table 4. Regression results of subindexes and damage

	B	Exp (B)	Significance (two-tailed)
Social resilience	2.649	6.234	0.017*
Economic resilience	1.500	4.084	0.010**
Infrastructure resilience	1.082	3.362	0.013*
Community capacity	0.773	2.066	0.030*
Institutional resilience	0.351	1.501	0.049*
Environmental	0.186	1.205	0.038*
Percent structures damaged	–4.867	28.139	0.001***

Note: Significance = 0.012; pseudo $R^2 = 0.282$ (Nagelkerke).
*Significant at 0.05.
**Significant at 0.01.
***Significant at 0.001.

The model results suggest that the amount of damage sustained is the strongest predictor of achieving a full recovery in the long term. Following damages sustained, the recovery process along the coast is to a large extent determined by social and then economic factors of resilience. Following Hurricane Katrina's impact, the disparities in the recovery process directly linked to social and economic resilience were distinguishable all along the coast. Along Biloxi's coastline, for instance, where nearly every business and multimillion-dollar home was destroyed, the more affluent business and homeowners received insurance settlements and began reconstruction quickly (Cutter et al. 2006). In the largely African American and Asian neighborhoods north of the coast in Biloxi, however, people were still living in houses that were condemned because they had no other option (Cutter et al. 2006). The contrast in the recovery between middle-class communities such as Ocean Springs and the marginalized of East Biloxi upholds this case in point.

In addition to the association of the social and economic parameters of resilience with the recovery process, the institutional, infrastructure, community, and environmental components show statistically significant relationships with achieving a full recovery outcome. The infrastructure subcomponent comprises the fourth largest predictor. The fifth, sixth, and seventh predictors are the community capacity, institutional, and environmental components of resilience, respectively.

Conclusion

There continues to be considerable interest from academia, governments, and the disaster risk reduction community in the topic of resilience. The formal establishment of the Office of Resilience within the U.S. National Security Council provides one example of the adoption of the resilience concept to make communities safer. It is within this context that the ability to measure resilience is increasingly being seen as a key step toward disaster risk reduction. The development of assessment standards for measuring resilience remains a challenge, however, partially because there is no agreed-on set of methods and metrics proposed in the literature for measuring the concept. Narrowing this research gap was the purpose of this work.

The primary motivation for this article was the discovery of a set of indicators that might provide the

best comparative assessment of disaster resilience among communities. By predicting recovery outcomes based on the differential recovery following Hurricane Katrina, the regression models determined that forty-one proxy variables might be suitable for measuring resilience based on analytical soundness and statistical significance. Educational attainment, employment status, homeownership, housing density, schools, the presence of religious organizations, and land-use change are just a few examples of indicators that might be important proxies for resilience measurement that were identified by the models. The extent to which these indicators predict a disaster recovery outcome is to a large extent the result of interacting conditions that are the product of the adverse impacts sustained, the social and economic characteristics of the people at risk, and contextual and localized attributes that were not captured by this research.

From a theoretical perspective, the contribution of this work is the melding of research on disaster resilience with composite indicators development. Using indicators such as those outlined within this article to assess what makes some communities more resilient than others permits comparisons across space and time and promotes (1) actions to reduce risk such as the development of public policies, (2) focused discussion on resilience building issues, and (3) ideas for integrated action. To support risk reduction, attention could be drawn to issues within communities in which a deeper analysis is needed. The exercise of computing an index in itself might be a viable way to make decision makers and stakeholders more aware of the factors affecting the resilience of communities they protect. For discussion, such metrics can help communities develop a common language for dialog, focusing discussions on matters directly relevant to risk reduction and recovery issues. Promoting ideas for integrated action relates directly to the multifaceted nature of resilience. Although composite indicators yield single values, they summarize complex realities that can foster awareness of the interconnections among different dimensions of a community's resilience so that actions to foster resilience are not taken exclusively in one area in isolation of others.

Because this is one of the first empirically based approaches aimed at measuring resilience, this research is not without areas of opportunity. Recommendations are summarized as follows:

- *Indicator selection*. The variable selection process for the development of composite indicators is subjective, and the results for this research were based on a single case study. The explanatory power of the regression models was moderately low to low, leaving large portions of the variance in model outputs unexplained. The latter provides fertile ground for continued work that focuses on alternate assessment standards such as approaches that make use of resilience scorecards that are highly customizable and make use of primary source data.
- *Spatial analytical considerations*. It is important to consider to what extent changes in scale and aggregation might lead to different, possibly contradicting results. At minimum, research should be conducted to better understand the association between potential resilience indicators and recovery processes at various scales; for example, region, county, tract, neighborhood, block, and individual levels. Such work will help researchers to better understand the scale at which important resilience processes operate and to understand whether there is an appropriate scale for resilience assessment.
- *Sensitivity and uncertainty in variable selection, weighting, and aggregation methods*. The outcomes and the robustness of composite indicators depend largely on the construction approaches selected, and resilience metrics are rarely accompanied by information regarding their uncertainties and sensitivities. The use of Monte Carlo–based uncertainty and sensitivity analysis is a viable method to gauge the robustness of the decisions made during the modeling process and should be used in future research to better understand which index construction methods might be most appropriate for measuring the concept.

The development of metrics for community resilience is still in the nascent stage, but there is considerable interest in these measures. Indicators such as those described in this research might be useful in providing a broad first assessment of resilience that lends to more detailed analyses for an increased understanding of place-specific factors affecting the resilience of populations. Although an agreed-on index of leading resilience indicators is yet to exist, perspectives from a multitude of disciplines show promising steps forward. It is within this context that an increased understanding of factors that enhance or hinder the resilience of communities provides an applicable step to initiating research interest, scholarly discussions, and the development of fine-tuned mechanisms to reduce natural hazard risk.

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Correspondence: GEM Foundation, c/o Eucentre, Via Ferrata 1, 27100 Pavia, Italy, e-mail: christopher.burton@globalquakemodel.org.