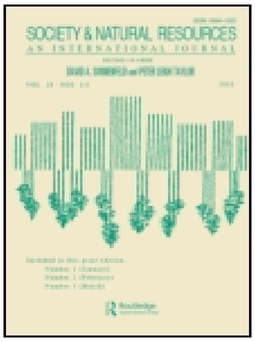

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Natural Disaster Response, Community Resilience, and Economic Capacity: A Case Study of Coastal Florida

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ABSTRACT

The strength and resiliency of regional economic and social structure play an important role in responding to and recovering from natural disasters. In this research, we address the economic resilience of coastal regions to natural disasters using county-level panel data. Results suggest that regions with stronger economies before the disaster experienced lower disaster losses. Thus, strengthening economic conditions before disasters strike can help minimize a region's vulnerability to future damage. Further, existing socio-economic conditions and social capital attributes improved local resiliency as long as exogenous baseline assumptions were well managed or maintained after a natural disaster. Policy implications of these findings are that increasing the adaptive capacity of counties should result in achieving wider societal goals that support resilient coastal development.

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adaptive capacity; climate change; disaster risk reduction; economic resilience; panel data analysis; social capital

The resilience of communities to the effects of natural disasters involves a complex set of interdependent social, economic, and environmental attributes. Community capacity to address sudden disruptions brought about by natural disasters reflects specific attributes of vulnerability (Magis 2010; Wilson 2012). Economic conditions and social capital within a community prior to sudden disruptions dictate the ability of community residents and local decision makers to garner necessary intergovernmental resources and foster leadership to coordinate effective rapid response. Such community capacity has been shown to be central to minimizing disaster losses (Waugh and Liu 2014).

Over the last four decades, coastal areas and barrier islands in the United States have become densely populated and are the current residence of nearly 50 million people. During this time period, the population of coastal regions has increased by 46% and is expected to continue growing at or above this rate (National Oceanic and Atmospheric Administration [NOAA] 2009). By 2015, estimates (NOAA 2009) suggest that population in these regions will increase by an additional 7.1 million individuals. These estimates further suggest that more than half of the U.S. population lives on roughly 17% of the land area along the coasts (Brody 2012). Between 1980 and 2003, the U.S. state of Florida has experienced a nearly 75% increase in population, the greatest percent of population change among all U.S. states (Crossett 2004). Further, more than 80% of Florida's residents live within 20 miles of the coast.

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Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/usnr.

Low-elevation coastal communities with high population concentrations, like those throughout Florida, are increasingly vulnerable to rising sea levels and various coastal hazards (Schapley and Schwartz 2014) brought about by strong storms (Beatley 2009). Since coastal areas are typically found with complex, interdependent infrastructure networks that tend to exhibit both higher property values and higher socioeconomic growth rates when compared to noncoastal areas, fast and effective recovery following disasters is extremely important. Studies focused on economic resilience to disasters offer useful results in addressing emergency management and public policy response. Among them, Rose, Oladosu, and Liao (2007), Rose et al. (2009), and Park et al. (2009) examined the role of local economies in resilience to the 9–11 World Trade Center terrorist event and utilized a microeconomic approach to resiliency analysis. By applying three production recapture factor functions (initial maximum, recapture output, general recapture factor) to disaster events, Park, Cho, and Rose (2011) found that business interruption period, damage state, and location characteristics have much to do with local economic resilience. However, few studies have been conducted using longitudinal data analysis on the role of economic capacity and social capital in resilience to natural disasters at the county level.

In this research, we examine the disaster experience of coastal areas within the U.S. state of Florida during the past 20 years using county-level panel data. Our objectives include (1) examining the relationship between economic resilience and hurricane damage affecting disaster-prone areas and (2) estimating the extent to which capacity or recovery among coastal areas is associated with hurricane intensity and resulting economic losses. This article is organized into five sections. Following this introduction, we provide a summary of the extant knowledge focused on disaster resilience with an emphasis on socioeconomic dimensions. Specifically, we are interested in better understanding the role of economic capacity and social capital in regional damage or loss due to hurricanes. Next, we outline our approach and methods used to empirically model these relationships. This is followed by a discussion of results suggested by our model. We conclude with a section that summarizes our work, provides limitations and caveats of this effort, and develops implications for public policy intent on improving the resilience of coastal areas to future natural disasters.

Literature Review

Adaptation to Climate Change

Every year, potentially damaging natural disasters (e.g., floods, droughts, temperature extremes, hurricanes, and earthquakes) occur around the world. In recent years, such natural events have been occurring more frequently and with greater intensity. Results of a recent study conducted by NOAA (2009) suggest that hurricane wind speeds have increased 5–10% as a result of a 2.2°C warming of the sea surface. Further studies attribute this increase to global climate change, which is expected to gradually increase the number and severity of these events in coming years (Prasad et al. 2009; Ruth and Ibarrarán 2009).

Natural disasters precipitated by global climate change can potentially lead to an incremental rise in the vulnerability of economic, social, and environmental systems that affect such human needs as food or water availability, shelter and transportation infrastructure, public and personal health, and ecosystems (Botzen and Van Den Bergh 2009).

Modern societies have become more vulnerable to social and economic damage from natural hazard events because the infrastructure has become more elaborate and populations have grown larger and are more concentrated (McBean and Ajibade 2009). Ultimately, more severe weather-related hazards caused by global climate change are expected to give rise to increasingly serious problems involving threats to human health, physical damage to infrastructure, economic losses, and alterations to biodiversity and ecosystem health.

Considering adaptation to climate change within the context of natural and social systems requires objectives that reflect a process of adjustment to anticipated futures (Turnbull et al. 2013). The Intergovernmental Panel on Climate Change (IPCC 2012, 5) proposed that such objectives involve policies that "moderate harm or exploit beneficial opportunity." Such adaptation refers to any adjustment that takes place in natural or human systems in accordance with expected vulnerabilities to natural disasters posed by climate change. For this reason, our work incorporates a number of characteristics that reflect how communities adapt to and prepare for natural disasters with a specific focus on disaster resilience.

Conceptualizing and Measuring Social, Ecological, and Economic Resilience

Vulnerability can be regarded as risk: the interaction between exogenous factors determined by the incidence and intensity of harm. Resiliency, on the other hand, deals with the ability to address (or react to) the impact of endogenous harmful factors. In an effort to assess both challenges and opportunities faced by a community in response to natural hazards, our work investigates economic resilience derived from the principles of social and ecological context.

With an emphasis on disaster-resilient communities, Ersing (2012, 103) noted that "resiliency is described as the ability to 'bounce back' or to return to a state of functioning that was in place prior to exposure to a significant stressor such as a natural hazard." Over time, this general concept of resilience has been applied to diverse social–ecological systems in accordance with thematic domains like social and economic change, ecosystems, environmental change, and spatial domains (Alexander 2013). If resilience is addressed in relation to social and environmental situations, it can be represented as the capacity of individuals or communities to deal with external shocks as a consequence of social, political, and ecological change (Norris et al. 2008; Peacock et al. 2012). In addition to this definition, social and environmental resilience persists with the same controls on the function and structure of diverse changes (Cutter et al. 2008). Also, recovery relates to the ability to bounce back from changes brought on by sudden events (Beatley 2009).

Given the dynamic association between social resilience and dependence on natural resources, resilience can be determined by institutional change, economic structure, and demographic change (Atkinson 2014). At the local or community level, social resilience encompasses elements that include formal sector employment, crime rates, and demographic change factors (e.g., mobility, migration). Regarding demographic change, in particular, significant population movement can reflect underlying stability and resilience.

Based on community resilience to natural disasters from a variety of research perspectives, variables for measuring resilience were described within ecologic, social, economic, institutional, infrastructure, and community systems categories (Cutter et al. 2008; Kapucu et al. 2013; Peacock et al. 2012). In particular, under the attributes of natural disasters and disaster risk reduction, ecologic and institutional systems were measured using floodplain area, soil permeability, wetlands acreage and loss, erosion rates, impervious surfaces, precipitation, biodiversity, participation in hazard reduction programs, hazard mitigation plans, emergency services, and zoning and building standards (Berke et al. 2014).

Social and economic resiliency components measured demographics, social networks and embeddedness, community value-cohesion, faith-based organizations or nonprofit organizations, employment, values of property, wealth generation, and municipal finance or revenues (Aldrich 2012; Demiroz and Hu 2014). Of particular interest among these indicators, Ersing (2012, 104) highlighted that "social networking can play an integral part in the ability of the local area to return to a pre-disaster state of functioning." In addition and with an emphasis on the role of social capital in disaster recovery, Aldrich (2012, 166) documented that addressing and enhancing local social capital will "create future plans that generate effective and efficient recovery and build resilient communities." Infrastructure resilience factors included lifelines and critical infrastructure, transportation networks, residential housing stock and age, and commercial and manufacturing establishments.

Economic metrics such as income and poverty rate are likewise important when assessing community resiliency. From a global perspective of disaster risk, recent assessment work (UN International Strategy for Disaster Reduction [UNISDR] 2013, 46) suggests that "in general higher-income countries and those with rapid economic growth over recent decades have successfully reduced their mortality risk. With economic development, capacities in disaster and emergency management generally improve." Further, disaster management and adaptation to climate change can enhance human capacity to cope with natural disasters. Variation in income within countries, in particular between urban and rural regions, is likewise thought to provide analogous results.

Research Design and Methods

Analytical Strategy

Based on the available literature in the field of disaster risk reduction and climate change adaptation, our empirical approach uses panel data analyses (e.g., negative binomial panel regression, dynamic panel data analysis) to address disaster resilience at the county level in the U.S. state of Florida. The relationship between climate change factors and natural disasters, as a part of human and ecological systems, has been investigated (cf. Brody 2008), and the variation of climate change risk can be estimated using climatological data. Likewise, the degree of response to a disaster depends on the occurrence and severity of the disaster (Ruth and Ibarrarán 2009). The response also depends on the local capacity to respond, the underlying infrastructure affected, and existing vulnerabilities.

In the recent disaster risk reduction literature (e.g., Wisner, Gaillard, and Kelmar 2012), vulnerability can be applied to diverse systems with "a predisposition of a person or group to be adversely affected" (Birkmann et al. 2013, 185). Disaster damage factors involve human damage such as fatalities and injuries and physical damage to property and crops (Kellenberg and Mobarak 2008). Predisaster regional economic vulnerability exists in relation to inherent, or existing resilience (Ruth and Ibarrarán 2009; Zhou et al. 2010). Empirically, regional socioeconomic factors include population density, education, unemployment rates, household incomes, and poverty incidence. In addition, geographic location is a central attribute of spatial modeling (Brody 2008).

Data Collection and Study Area

Using the Gulf of Mexico and Atlantic Coast of Florida as the study geography for this research, longitudinal data at the county level for geographical and urban influence characteristics and economic conditions as well as disaster impacts between 1990 and 2009 were collected. Further, data for each of the 67 counties within the study area included coastal proximity to the Atlantic Ocean or Gulf of Mexico, ecosystem characteristics including biodiversity, watersheds, and wetlands, tourist destinations such as national parks and preserves, and level of urbanization. The study time period of 1990 to 2009 was used and appears appropriate due to the ability to obtain reports from a variety of databases and the incidence of severe damage from hurricanes (e.g., Hurricanes Earl, George, Frances, and Jeanne). The increasing frequency and severity of hurricanes related to climate change along the Gulf of Mexico and Atlantic Coasts has given rise to increasing human losses and physical damages (Prasad et al. 2009). Finally, detailed county-level demographic, housing, and economic information was collected from the U.S. Census Bureau (USCB 2013).

Based on review of the disaster literature (e.g., Cutter et al. 2008; Norris et al. 2008; Ross 2013; Strobl 2011; Waugh and Liu 2014), variables used in this analysis are presented in Table 1. As a dependent variable, the U.S. dollar value of median household income (adjusted for inflation in 2002) aggregated to the county level was log transformed in order to better approximate a normal distribution. The demographic and housing characteristic variables as controlling and independent variables during the last 10 years (from 2000 to 2009) included educational attainment (percent of population with a bachelor's degree), race (percent of white population), age (percent of population over 65 years), and housing characteristics (percent of housing units built in 1989 or earlier, percent of housing units in structure with mobile, percent of homeownership).

Following research that suggests a positive role for social capital in enhancing social resilience from natural disasters (e.g., Aldrich 2012; Aldrich and Meyer 2014; Deshkar et al. 2011; Rivera and Settembrino 2013; Ross 2013; Waugh and Liu 2014), voter turnout, political party support (percent of voter turnout and political party selected in presidential general election in 2004), and civic organizations (number of civic organizations per 10,000 population), including religious, grant-making, civic professional, and similar organizations—NAICS code 813) served as proxies for social capital characteristics. These data were collected from the official website Dave Leip's Atlas of U.S. Presidential Elections (DLAUSPE 2008) and USCB (2014).

Geographic characteristics specifying whether or not the study area was a contiguous coast or coastline and urbanization characteristics were collected from the National Ocean Economics Program (NOEP 2011) at the Center for the Blue Economy and the U.S. Department of Agriculture Economic Research Service (USDA ERS 2012). As noted earlier, urban influence attributes (metropolitan status) are also associated with key economic characteristics that influence vulnerability and resiliency. Information on intensity, frequency, and speed of hurricanes during the study period was collected from NOAA.

Hurricane intensity was derived by hurricane category using the Saffir–Simpson Hurricane Scale. In addition, county-level data on damage or loss after a hurricane occurred (fatalities, injuries, property damage, and crop damage) were obtained from the Spatial Hazard Events and Losses Database for the United States (SHELDUS 2010) at the University of South Carolina Hazard Research Lab. Compiled from U.S. government sources such

Table 1. Variables definitions, measurement, and descriptive statistics.

Variable name	Description and measurement		All counties* ($n = 1{,}340$) Mean	All counties* SD	Non-damaged counties** ($n = 160$) Mean	Non-damaged counties** SD	Damaged counties*** ($n = 220$) Mean	Damaged counties*** SD	Data source
			Economic characteristics						
Unemploy[c]	Unemployment rate	%	5.76	2.57	5.13	2.11	5.75	2.44	USCB
Income	Median household income adjusted to 2002 dollars	US$	33,803.58	8,699.2	42,989.99	9,548.54	40,985.22	6,512.09	
log Income[a]	Natural logarithm of median household income adjusted to 2002 dollars	US$	4.51	0.10	4.62	0.09	4.60	0.06	
Poverty	People of poverty/population	%	15.76	5.03	12.64	4.44	12.48	3.71	
GINI[b]	Gini index (based on median household income)	scale			44.00	4.13	45.54	2.92	
			Geographical and urban influence characteristics						
Metro	1 = metro, 0 = non-metro	dummy	0.56	0.49	0.62	0.48	0.81	0.38	USDA ERS
Coast	1 = continuous coast or coastline, 0 = Otherwise	dummy	0.50	0.50	0.31	0.46	0.81	0.38	NOEP
			Demographic and housing characteristics[c]						
Bachelor	Percent of adult population (over 25) with bachelor degree and over	%			22.40	8.49	22.47	6.77	USCB
White	Percent of white population	%			83.23	7.66	83.72	6.57	
Age	Percent of population over the age of 65 years	%			18.88	8.99	22.45	5.97	
Housing age	Percent of housing built in 1989 or earlier	%			57.58	13.36	59.20	10.95	
Mobile home	Percent of housing units in structure with mobile	%			18.19	11.65	14.69	12.73	
Homeownership	Percent of homeownership	%			73.01	7.82	73.56	6.14	
			Social capital and political characteristics[c]						
Voter	Percent of voter turnout in presidential election in 2004	%			44.66	7.74	45.06	7.99	DLAUSPE
Political	1 = Democratic party, 0 = Republican party (based on 2004 presidential general election)	dummy			0.12	0.33	0.22	0.42	
Civic	Number of civic organizations (consisting of religious, grantmaking, civic, professional, and similar organizations) per 10,000 population				9.12	1.89	14.80	16.31	US CBP

				Disaster impact characteristics					
Intensity	Hurricane category (0 to 4)	scale	0.12	0.59			0.25	0.87	NOAA n.d.
Yr1998	Hurricanes Earl and George occurred (1 = 1998 year, 0 = Otherwise)	dummy	0.05	0.21					
Yr2004	Hurricanes Frances and Jeanne occurred (1 = 2004 year, 0 = Otherwise)	dummy	0.05	0.21			0.1	0.30	
Fatality[d]	Fatalities per population	person	0.04	0.30			0.05	0.26	SHELDUS
Injury[d]	Injuries per population	person	0.67	9.58			3.58	23.29	
Property[d]	Average property losses	US$	2.24e+07	1.77e+08			9.59e+07	3.91e+08	
log Property[d]	Natural logarithm of average property losses	US$	7.35	8.24			7.98	8.59	
				Damage year interaction[e]					
Property × Yr 2005	Interaction term between average property losses and year (1 = 2005, 0 = Otherwise)						4.60e+07	3.35e+08	
Property × Yr 2006	Interaction term between average property losses and year (1 = 2006, 0 = otherwise)						0	0	
Property × Yr 2007	Interaction term between average property losses and year (1 = 2007, 0 = otherwise)						0	0	
Property × Yr 2008	Interaction term between average property losses and year (1 = 2008, 0 = otherwise)						0	0	

Note. [a]Dependent variable in dynamic panel model.

[b]Variable used in addressing the relationship between economic inequality and disaster losses.

[c]Control variables used in negative binomial panel regression and dynamic panel model; *67 counties during 20 years (1990–2009), **16 counties not damaged by hurricanes Frances and Jeanne during 10 years (2000–2009), ***22 counties damaged by hurricanes Frances and Jeanne during 10 years (2000–2009).

[d]Dependent variables for negative binomial panel regression.

[e]Variables for limited study areas (22 counties) affected by hurricanes Frances and Jeanne occurred in 2004: *67 counties during 20 years (1990–2009), **16 counties not damaged by hurricanes Frances and Jeanne during 10 years (2000–2009), ***22 counties damaged by hurricanes Frances and Jeanne during 10 years (2000–2009), × interaction term.

as the U.S. Geological Survey and the National Climatic Data Center, the SHELDUS database used estimates obtained through observation or secondary reports.

Analytical Models and Diagnostics

Static panel analysis was initially utilized to develop a model of the data over the study period. Accounting for 67 counties (i.e., number of groups in Table 2) and 20 points in time, the total sample size is 1,340. Regional economic attributes for each area i during study period t were specified as $Unemploy_{it}$, $Income_{it}$, and $Poverty_{it}$. *Metro* and *Coast* are represented as dummy or indicator variables that depict geographic and urban influence characteristics in the study area. *YR1998* and *YR2004* reflect dummy variables that denote data from the years when hurricanes Earl and George (1998) and Frances and Jeanne (2004) affected the study areas. A statistically significant Hausman test result indicated that the random effects were inconsistent and the fixed effects were more appropriate.

Table 2. Fixed-effect models using negative binomial panel regression.

	Fatality	Injury	Property		
	(1)	(2)	(3)	(4)	(5)[d]
Economic characteristics					
Unemploy	0.010** (0.070)	0.017** (0.051)	−0.081** (0.029)	−0.099** (0.033)	−0.369*** (0.097)
Unemploy × Yr1998				0.075 (0.078)	
Unemploy × Yr2004				0.130 (0.196)	−0.965* (0.412)
log Income	3.878 (3.555)	2.171 (2.533)	−3.526*** (0.907)	−3.375*** (0.964)	−2.739*** (0.652)
Income × Yr1998				0.001 (0.001)	
Income × Yr2004				−0.001*** (0.001)	−0.002** (0.001)
Poverty	0.049** (0.068)	0.001* (0.045)	0.023 (0.020)	0.024 (0.021)	0.026 (0.029)
Poverty × Yr1998				0.128* (0.066)	
Poverty × Yr2004				0.291** (0.085)	0.417** (0.196)
Geographical and urban influence characteristics					
Metro	0.387 (0.471)	−0.453 (0.292)	0.050 (0.150)	0.159 (0.152)	0.421 (0.237)
Coast	0.368** (0.380)	0.336* (0.257)	0.769*** (0.132)	0.779*** (0.135)	1.562** (0.296)
Demographic and housing characteristics					
Bachelor					−0.010 (0.023)
White					−0.035 (0.081)
Age					0.020 (0.032)
Housing age					0.017* (0.027)
Mobile home					0.009* (0.019)
Homeownership					−0.087 (0.034)
Social capital and political characteristics					
Voter					−0.040* (0.080)
Political					−2.455 (1.047)
Civic					−0.002* (0.001)
Disaster impact characteristics					
Intensity	0.277** (0.132)	0.167* (0.124)	0.497*** (0.073)	0.540*** (0.073)	0.927*** (0.162)
Damage year interaction[a]					
Yr1998	13.289 (684.413)	0.782** (0.377)	0.785*** (0.186)	−3.208 (2.720)	
Yr2004	2.088 (1.700)	1.873*** (0.452)	0.324 (0.253)	9.819*** (2.732)	10.865* (9.324)
Number of observations	1,340[b]	1,340[b]	1,340[b]	1,340[b]	220[c]
Log-likelihood	−136.56	−268.20	−5,966.32	−5,954.45	−580.03
Wald chi-squared	17.37**	24.42**	164.90***	210.87***	215.56***

Note. Robust standard errors in parentheses. *Significant at 10%. **Significant at 5%. ***Significant at 1% (two-tailed test).
[a]Variables without interaction term *Property*.
[b]For 67 counties during 20 years (1990–2009).
[c]For 22 damaged counties from hurricanes Frances and Jeanne during 10 years (2000–2009).
[d]Dependent variable is log *Property* × interaction term.

Since the distribution of the dependent variable was positively skewed (i.e., the mean and standard deviation of *Fatality* is 0.04 and 0.30 described in Models 1 and 2 of Table 2), a negative binomial panel regression was employed.

In order to include lags of the dependent variable as covariates, unobserved panel-level effects and fixed or random dynamic panel effects were employed (Baltagi 2008). Using dynamic panel analysis, a dependent variable was defined as the regional economic attribute for each designated study area i ($i = 1$ to 22, damaged counties, and 16 nondamaged ones) and designated study year t ($t = 2000$–2009) associated with before and after hurricanes Frances and Jeanne (2004). Consistent estimators were found by employing the generalized method of moments approach following Arellano and Bond (1991). Through first-differencing for removing panel-level effects and instruments for forming moment conditions, the estimators can be formulated with many panels and few periods (Baltagi 2008). Based on this method, we compared the degree of disaster resilience of damaged to nondamaged counties before and after natural disasters with an emphasis on lagged dependent variables.

In an effort to ensure statistical assumptions were met, diverse analysis diagnostics were conducted before making estimations. First, to investigate whether or not the panel data used in this study were stationary, an Augmented Dickey–Fuller panel unit root test was employed. Results suggested that except for *Fatality, Injury, Property*, and *Unemploy*, all the variables shown in Table 1 were not stationary at the 90% level of confidence. The Johansen co-integration test for variables revealed no problems with spurious regression. In addition, in order to address the potential for heteroskedasticity and serial correlation among these panel data, a generalized least squares (GLS) estimation approach with Huber and White robust estimators was employed (see Tables 2 and 3). To check the validity of this model and test for multicollinearity among the independent variables (including *Poverty, Unemploy*, and *log Income* variables), a variance inflation factor (VIF) was used. By parsimonious selection and removal of variables with high levels of multicollinearity among independent variables, our final model was tested resulting in a VIF of 4.67. This VIF is within the acceptable limits common to ensure robust estimation results (below a threshold of 5 as specified by Studenmund 2006). Furthermore, since this study relied on county-level data as the level of empirical analysis, we diagnosed the existence of spatial autocorrelation within the regression residual by using Moran's *I* and the Lagrange multiplier test (Anselin 2009). These tests indicated that there was no spatial dependence in spatially lagged dependent variables.

Modeling Resiliency

Descriptive Statistics

Definitions and descriptive statistics for economic, geographic and urban influence, demographic and housing, social capital, and political characteristics, as well as disaster impact attributes for the study area, are presented in Table 1. To better approximate disaster resilience, three columns for study area counties are presented based on whether the county was influenced by a natural disaster. The third column, including the damage year interaction variables (*Property* × *YR 2005* – *Property* × *YR 2008*), was used to address the response of regional economies to hurricane losses between nondamaged and damaged

Table 3. Dynamic panel data analysis (Arellano and Bond [1991] estimation).

	Damaged counties[a]			Nondamaged counties[b]	
	(6)	(7)	(8)	(9)	(10)
			Economic characteristics		
Unemploy (lag1)	−0.006*** (0.001)	−0.007** (0.002)	−0.013** (0.002)	−0.008*** (0.001)	−0.007* (0.002)
Unemploy (lag2)	−0.007*** (0.001)	0.001 (0.001)	0.001 (0.001)	−0.008*** (0.001)	−0.007* (0.002)
Poverty (lag1)	0.0002 (0.001)	0.0005 (0.0009)	0.0011 (0.001)	0.002 (0.002)	0.005 (0.001)
Poverty (lag2)	−0.0002*** (0.0005)	0.0001 (0.0004)	0.0023 (0.003)	0.001 (0.001)	0.003 (0.002)
log Income (lag1)	−9.24e−06*** (2.60e−06)	−3.69e−06 (4.07e−06)	−5.78e−06 (3.58e−06)	−5.39e−06** (2.24e−06)	−4.27e−06* (1.67e−06)
log Income (lag2)	4.30e−06*** (1.10e−06)	−3.17e−05** (9.92e−07)	−5.67e−05** (5.18e−06)	3.86e−06** (1.38e−06)	2.37e−05* (1.09e−05)
			Demographic and housing characteristics		
Bachelor			0.012* (0.002)		0.010* (0.002)
White			0.009* (0.003)		0.005 (0.002)
Age			−0.008 (0.003)		−0.012 (0.002)
Housing age			−0.063 (0.009)		−0.044 (0.009)
Mobile home			−0.026 (0.008)		−0.019 (0.007)
Homeownership			0.039* (0.008)		0.012** (0.001)
			Social capital and political characteristics		
Voter			0.019** (0.002)		0.022 (0.003)
Political			−0.011 (0.002)		−0.009 (0.002)
Civic			0.025* (0.003)		0.067* (0.012)
Disaster impact characteristics					
Intensity		−0.003 (0.002)	−0.003 (0.002)		
			Damage year interaction		
Property × Yr2005		−0.096*** (0.013)	−0.067* (0.013)		
Property × Yr2006		−0.076*** (0.015)	−0.053* (0.010)		
Property × Yr2007		−0.047** (0.014)	−0.032* (0.002)		
Property × Yr2008		0.003** (0.002)	0.002* (0.001)		
Number of observations	220[a]	220[a]	220[a]	160[b]	160[b]
Wald chi-squared	294,727.18***	1,475.00***	1,532.12**	2,582.60***	1,329.11***

Note. Dependent variable is *log Income*. Robust standard errors in parentheses. *Significant at 10%. **Significant at 5%. ***Significant at 1% (two-tailed test).

[a]For 22 damaged counties from hurricanes Frances and Jeanne during 10 years (2000–2009).

[b]For 16 nondamaged counties from hurricanes Frances and Jeanne during 10 years (2000–2009).

counties from 2005 to 2008. Three economic variables measuring resilience were selected: unemployment rate, median household income, and per capita poverty rate for each jurisdiction in the sample. The average median household income, adjusted to 2002 year dollars, ranged from a minimum of $33,800 (2002 USD) to a maximum of $43,000 (2002 USD).

The second panel stated that with regard to geographic and urban influence characteristics, two variables depicted the degree of spatial influence relative to natural disaster impact measured on a discrete scale. More specifically, about 80% of counties among all study areas influenced by distinct natural disasters (hurricanes Frances and Jeanne) during 2000 to 2009 had coastal and urban characteristics. People and property concentrations in coastal areas led us to not only examine the linkage between disaster damage and economic resilience but also the extent of capacity recovery among coastal areas depending on hurricane intensity and economic loss associated with such disaster. The third and fourth panels show differences between nondamaged counties and damaged counties from hurricanes Frances and Jeanne (during 2000–2009) measured using a variety of demographic and housing, social capital, and political characteristics. In particular, damaged counties had higher percentages of population over the age of 65 years when compared to nondamaged counties. Regarding one important form of social capital, damaged counties had about 50% more civic organizations than nondamaged counties.

In the last panel, to correct for these problems that could lead to potential correlation, variables including *Fatality* and *Injury* were adopted as injuries or fatalities per capita to proxy human loss to natural disaster. Otherwise, densely populated areas would be more likely to have higher injuries simply because of the increased population and risk factors such as poverty and unemployment. In addition, hurricane loss variables such as *Property* and *Crop* show the average amount of losses by various hurricanes.

Determinants of Resiliency

To address the determinants of natural disaster resilience, a negative binomial panel regression was employed following Kellenberg and Mobarak (2008). Specifically, the dependent variable reflected the number of people killed or injured by hurricanes Charley, Dennis, Earl, Frances, George, Ivan, Jeanne, Opal, and Wilma, each of which affected the study areas during the study period.

The fixed-effects model was predicted based on three different types of human and property losses (i.e., fatality, injury, and property damage) resulting from natural disasters. Models 1 and 2 in Table 2 focus on human fatality and injury as a natural disaster loss in counties struck by hurricanes. Results suggested that except for the *Income, Unemploy, Poverty, Coast*, and *Intensity*, variables were related positively and significantly to *Fatality* and *Injury* (the dependent variables). In other words, higher rates of unemployment and poverty in conjunction with higher intensity of natural disasters combined with the location of the disaster on a contiguous coast led to greater human losses during natural disasters. This finding confirms the results of Strobl (2011), who documented that disaster loss decreases as levels of regional socioeconomic conditions improve at the county level.

Lower socioeconomic condition is likely to be positively associated with human losses caused by natural disasters (Toya and Skidmore 2007). For this reason, counties displaying better socioeconomic conditions are expected to experience lower disaster losses. The county that undergoes lower damage losses can be said to be more resilient than those that have higher losses (McBean and Ajibade 2009). On the other hand, in Models 3, 4, and 5 (focused on property damage as residential loss), the *Property* variable suggested that the coefficient of *log Income* was negative and significant at the 0.01 level. This finding is consistent with Kellenberg and Mobarak (2008) and Zhou et al. (2010), who claim that higher income leads to minimized disaster losses and is inversely correlated with property losses caused by natural disasters. We note, in particular, that this empirical result was found in Model 5, which included a variety of control variables such as demographic and housing characteristics and social capital characteristics.

Despite the limited geographic (22 damaged counties from hurricanes Frances and Jeanne) and temporal scope (10 years, 2000–2009), relationships between *Property* and *Housing age* and *Mobile home* were positive and significant at the 0.1 levels. Further, there was insignificant association between *Poverty* (as a factor of community economic situation) and *Property* (as an indicator of disaster losses), but we should be aware that poverty rate had a positive correlation with property losses from natural disaster. We can assume that the poorer a community is, the more likely it is that a community suffers greater losses from natural disasters.

With respect to social capital and disaster resilience, our results are mixed. While results from Portney (2003) suggested significant political affiliation affects (with an assumption that politicians who are more responsive to disaster damage better prepare or compensate the communities), our empirical results do not. However, confirming recent empirical results of Aldrich (2012), Aldrich and Meyer (2014), Kage (2011), and Chamlee-Wright and Storr (2009), our Model 5 suggests significance with two variables (*Voter* and *Civic*) that reflect social capital (see Table 2). Our model results suggest statistically significant inverse relationships between both voter turnout and number of civic organizations with property loss. This is summarized for voter turnout in Figure 1. Note from this figure that as voter turnout increased, property damage resulting from disaster events decreased (a similar result exists for civic organizations). Neighborhoods that are more politically active and exhibit well-connected local institutions for regular contact among residents are logically more apt to exchange useful disaster-relevant information prior to and during disaster situations. In essence, local social capital attributes as proxied by both voter turnout and civic organizations were important underlying factors in decreasing vulnerability and further promoting resilience.

Response to Natural Disaster Events

As a second estimation method, a dynamic panel data analysis was used to compare the economies of counties damaged by natural disasters to those that were not. Household income (*log Income*) was determined by the lagged dependent variable and resilience determinants. Empirical results for the lagged resilience determinants are described in Table 3. The study areas were divided into two groups according to hurricane damage experienced during the 10 years from 2000 to 2009. One group included the 22 counties damaged by two hurricanes, Frances and Jeanne (2004), while the other group was composed of 16 counties not affected by the same hurricanes.

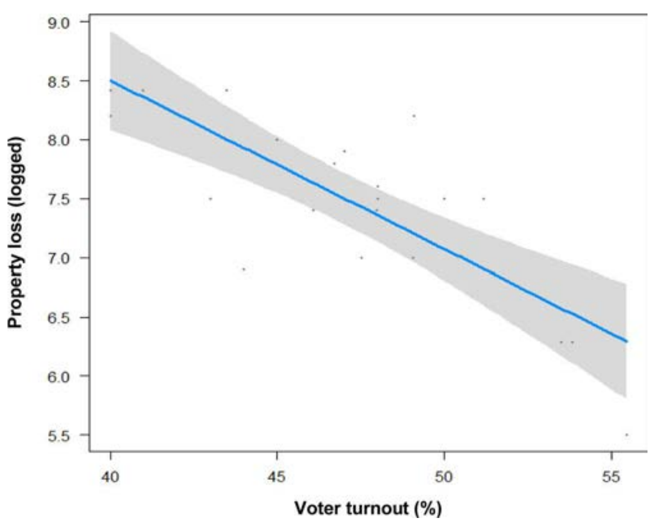

Figure 1. Relationship between social capital attribute and disaster losses. Dots indicate 22 damaged counties in study areas from hurricanes Frances and Jeanne during 2000 to 2009; shaded area indicates confidence interval.

As predicted, unlagged residential losses had a negative influence on household income as part of the economic indicators in all twenty-two counties damaged by hurricanes. In addition to physical damage, results summarized in Table 3 suggested that the coefficient of the hurricane intensity variable (*Intensity*) was not significant in Models 7 and 8. Both the areas experienced a significantly negative household income result. Further, the estimated negative coefficients in Models 6 and 7, respectively, suggest that the postdisaster economic condition of counties affected by natural disasters was lower than those of counties damaged by the same disaster. Specifically, Models 7 and 8 captured outcomes of hurricane damage better, showing its influence on economic status (i.e., *log Income*) from 2005 to 2008. In 2005, the first year after hurricanes Frances and Jeanne, every 1% increase in hurricane damage (in particular, *Property*) led to a 9.6% (6.7% in Model 8) decrease in household income. This negative effect of natural disaster damage remained in the following years. However, the net influence gradually decreased. In 2006, every 1% of hurricane damage resulted in 7.6% (5.3% in Model 8) loss in our logged income metric.

By addressing economic and distributional impacts of climate change-related disasters within a society, Ibarrarán and Ruth (2009, 46–47) pointed out that "natural disasters tend to exacerbate existing differences across a population, often increasing poverty levels and income disparity." In this sense, counties already suffering from poor economic conditions are relatively more severely impacted. Among various economic resilience factors, evenly distributed economic resources can be regarded as a key aspect of resilient communities (Kapucu and Özerdem 2013). Conceptual positive associations between economic inequality (*GINI* variable) and natural disaster losses (log *Property* damage) are appropriate and important elements of disaster resiliency.

Conclusions

In this research, we empirically estimated the association between community resilience and natural disasters using Florida counties as a case example. Our empirical approach used panel data at the county level from secondary sources. Similar to results of previous studies, coastal counties with stronger economies and better social conditions before the disaster experienced lower disaster losses. This association between economic characteristics and natural disaster damage suggests the following implications. If a county has higher rates of unemployment and poverty and lower household income before the disaster occurs, our results suggest that it will undergo higher levels of human loss during natural disasters than a county having stronger economic and social characteristics. In addition, our results suggest that resiliency is indeed a disaster effect; counties affected by disaster shocks take longer to return to normality (i.e., are less resilient) than nonaffected counties. For this reason, more effort to strengthen social and economic characteristics before natural disasters can help minimize resulting damage (Zhou et al. 2010) and promote community resilience to natural disasters (Aldrich and Meyer 2014). This is particularly true for attributes of social capital, proxied in our models using voter turnout and number of civic organizations.

In terms of our contribution to the conceptual understanding of community resilience and global climate change, two overarching results were found. First, more severe weather-related hazards (i.e., greater intensity and frequency of hurricanes) result in increasingly serious economic problems for society. For this reason, adaptation with resiliency to climate change needs to be a central priority for public policy. Second, such adaptation needs to significantly relate to economic resilience brought about by unexpected natural disasters. Increasing the adaptive capacity and resilience of communities through improved public participation and social networking should result in achieving broader societal goals associated with sustainable development (Berkes and Ross 2013).

Although this work offers empirical insights into community resilience to natural disasters, it is still quite preliminary and contains important limitations. As with many studies utilizing standardized secondary data, we were constrained by the limited number of analytical variables. It is difficult to use existing data to address individual-level perceptions or behavioral responses reflective of diverse economic and social variables affected by natural disasters. Future research needs to include data on resident or community risk perceptions (e.g., Newman et al. 2014). Examples of this include the extent to which natural disasters affect perceptions of social and economic inequality and social capital (or social networks). This could be done through various primary data collection mechanisms within affected study areas (e.g., surveys, structured interviews, focus groups, Delphi, etc.).

In addition, given that there are spatial and temporal attributes of social and economic status influenced by unexpected natural disasters, we were limited by nonlinear causality and spatial heterogeneity in addressing disaster resilience due to the lack of efficiently scaled geographic data sets. In order to overcome this limitation and conduct truly meaningful spatial and temporal analysis, future research needs to utilize spatial data at more microlevels (e.g., subcounty geographic units) across broader time frames. Given that this work did not explicitly incorporate natural hazard mitigation plan quality, our results are limited in addressing effective planning responses. Future research needs to include assessment of natural hazard plans.

From the perspective of statistical analysis, while we took care to appropriately specify our models, heteroscedasticity could remain problematic. Our research tested the assumption that the poorer a community is, the more likely it is that a community suffers higher levels of natural disaster loss. Possible solutions to these analytical problems could specify empirical models using dummy variables that divide communities into high and low damage to test income and other economic conditions in explaining disaster loss.

Despite these limitations, our findings can be useful for reflection on disaster resilience that includes adaptation to climate change in coastal areas. Theoretically sound empirical approaches can assist public policymakers in better understanding natural disaster planning. This, in turn, will allow for improved social and economic resilience leading to higher levels of coastal region sustainability. In this way, planners can more effectively implement policies to ameliorate future negative impacts to coastal communities.

References

Aldrich, D. P. 2012. *Building resilience: Social capital in post-disaster recovery*. Chicago, IL: University of Chicago Press.

Aldrich, D. P., and M. A. Meyer. 2014. Social capital and community resilience. *American Behavioral Scientist* 59:1–16. doi:10.1177/0002764214550299

Alexander, D. E. 2013. Resilience and disaster risk reduction: An etymological journey. *Natural Hazards and Earth System Sciences* 13:2707–16. doi:10.5194/nhess-13–2707-2013

Anselin, L. 2009. Spatial regression. In *The SAGE handbook of spatial analysis*, ed. A. S. Fotheringham and P. A. Rogerson, 255–75, Los Angeles, CA: SAGE.

Arellano, M., and S. Bond. 1991. Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies* 58:277–97. doi:10.2307/2297968

Atkinson, C. L. 2014. *Toward resilient communities: Examining the impacts of local governments in disasters*. New York, NY: Routledge.

Baltagi, B. H. 2008. *Econometric analysis of panel data*. Chichester, UK: Wiley.

Beatley, T. 2009. *Planning for coastal resilience: Best practices for calamitous times*. Washington, DC: Island Press.

Berke, P. R., W. Lyles, and G. Smith. 2014. Impacts of federal and state hazard mitigation policies on local land use policy. *Journal of Planning Education and Research* 34(1):60–76. doi:10.1177/0739456X13517004

Berkes, F., and H. Ross. 2013. Community resilience: Toward an integrated approach. *Society & Natural Resources* 26:5–20. doi:10.1080/08941920.2012.736605

Birkmann, J., M. Garschagen, A. Lopez, M. Pelling, N. Q. Maqami, and Q. Yu. 2013. Urban development, climate change and disaster risk reduction: Interaction and integration. In *Megacities and the coast: Risk, resilience and transformation*, ed. M. Pelling and S. Blackburn, 173–99. New York, NY: Routledge.

Botzen, W. J. W., and J. C. J. M. Van Den Bergh. 2009. Managing natural disaster risks in a changing climate. *Environmental Hazards* 8:209–25.

Brody, S. D. 2008. *Ecosystem planning in Florida: Solving regional problems through local decision-making*. Burlington, VT: Ashgate.

Brody, S. D. 2012. Land-use change and increased vulnerability. In *Lessons from Hurricane Ike*, ed. P. B. Bedient 138–55. College Station, TX: Texas A&M University Press.

Chamlee-Wright, E., and V. H. Storr. 2009. Club goods and post-disaster community return. *Rationality and Society* 21:429–58. doi:10.1177/1043463109337097

Crossett, K. M. 2004. *Population trends along the coastal United States: 1980–2008*. U.S. Department of Commerce, National Oceanic and Atmospheric Administration, National Ocean Service, Management and Budget Office. Washington, DC: Special Projects, Government Printing Office.

Cutter, S. L., L. Barnes, M. Berry, C. Burton, E. Evans, E. Tate, and J. Webb. 2008. A place-based model for understanding community resilience to natural disasters. *Global Environmental Change* 18:598–606. doi:10.1016/j.gloenvcha.2008.07.013

Dave Leip's Atlas of U.S. Presidential Elections (DLAUSPE). 2008. Aggregated official results of past elections. http://uselectionatlas.org (accessed August 10, 2014).

Demiroz, F., and Q. Hu. 2014. The role of nonprofits and civil society in post-disaster recovery and development. In *Disaster and development: Examining global issues and cases*, ed. N. Kapucu and K. T. Liou, 317–30. Cham, Switzerland: Springer.

Deshkar, S., Y. Hayashia, and Y. Mori. 2011. An alternative approach for planning the resilient cities in developing countries. *International Journal of Urban Science* 15(1):1–14. doi:10.1080/12265934.2011.580148

Ersing, R. L. 2012. Using social networks to build disaster-resilient communities: The strategy of CODE ONE. In *Surviving disaster: The role of social networks*, ed. R. L. Ersing and K. A. Kost, 100–13. Chicago, IL: Lyceum.

Ibarrarán, M., and M. Ruth. 2009. Climate change and natural disasters: Economic and distributional impacts. In *Distributional impacts of climate change and disasters*, ed. M. Ruth and M. Ibarrarán 46–66. Northampton, MA: Edward Elgar.

Intergovernmental Panel on Climate Change. 2012. Summary for policymakers. In *Managing the risks of extreme events and disasters to advance climate change adaptation: A special report of working groups I and II of the Intergovernmental Panel on Climate Change*, ed. C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G. K. Plattner, S. K. Allen, M. Tignor, and P. M. Midgley, 3–21. New York, NY: Cambridge University Press.

Kage, R. 2011. *Civic engagement in post war Japan: The revival of a defeated society*. Cambridge, UK: Cambridge University Press.

Kapucu, N., C. V. Hawkins, and F. Rivera. 2013. Disaster resiliency: Interdisciplinary perspectives. In *Disaster resiliency: Interdisciplinary perspectives*, ed. N. Kapucu, C. V. Hawkins, and F. I. Rivera, 1–14. New York, NY: Routledge.

Kapucu, N., and A. Özerdem. 2013. Community resilience in disaster response. In *Managing emergencies and crisis*, ed. N. Kapucu and A. Özerdem, 87–112. Burlington, MA: Jones & Bartlett Learning.

Kellenberg, D. K., and A. M. Mobarak. 2008. Does rising income increase or decrease damage risk from natural disasters? *Journal of Urban Economics* 63:778–802. doi:10.1016/j.jue.2007.05.003

Magis, K. 2010. Community resilience: An indicator of social sustainability. *Society & Natural Resources* 23:401–16. doi:10.1080/08941920903305674

McBean, G., and I. Ajibade. 2009. Climate change, related hazards and human settlements. *Current Opinion Environmental Sustainability* 1:179–86. doi:10.1016/j.cosust.2009.10.006

National Ocean Economics Program (NOEP). 2011. Market data. http://oceaneconomics.org/Market/coastal/coastalEcon.asp (accessed November 12, 2013).

National Oceanic and Atmospheric Administration. 2009. Population trends along the coastal United States 1980–2008. http://oceanservice.noaa.gov/programs/mb/pdfs/coastal_pop_trends_complete.pdf (accessed September 10, 2012).

National Oceanic and Atmospheric Administration. n.d. http://www.noaa.gov (accessed December 15, 2012).

Newman, S. M., M. S. Carroll, P. J. Jakes, D. R. Williams, and L. L. Higgins. 2014. Earth, wind, and fire: Wildfire risk perceptions in a hurricane-prone environment. *Society & Natural Resources* 27:1161–76. doi:10.1080/08941920.2014.918234

Norris, F. H., S. P. Stevens, B. Pfefferbaum, K. F. Wyche, and R. L. Pfefferbaum. 2008. Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *American Journal of Community Psychology* 41:127–50. doi:10.1007/s10464-007-9156-6

Park, J., J. Cho, and A. Rose. 2011. Modeling a major source of economic resilience to disasters: Recapturing lost production. *Natural Hazards* 58(1):163–82. doi:10.1007/s11069-010-9656-9

Park, J., P. Gordon, E. Jun, J. E. Moore II, and H. W. Richardson. 2009. Identifying the regional economic impacts of 9/11. *Peace Economics, Peace Science and Public Policy* 15(2): Article 6. doi:10.2202/1554-8597.1162

Peacock, W. G., S. V. Zandt, D. Henry, H. Grover, and W. Highfield. 2012. Using social vulnerability mapping to enhance coastal community resiliency in Texas. In *Lessons from Hurricane Ike*, ed. P. B. Bedient, 66–81. College Station, TX: Texas A&M University Press.

Portney, K. E. 2003. *Taking sustainable cities seriously: Economic development, the environment, and quality of life in American cities*. Cambridge, MA: MIT Press.

Prasad, N., F. Ranghieri, F. Shah, Z. Trohannis, E. Kessler, and R. Sinha. 2009. *Climate resilient cities: A primer on reducing vulnerabilities to disasters*. Washington, DC: World Bank.

Rivera, F. I., and M. R. Settembrino. 2013. Sociological insights on the role of social capital in disaster resilience. In *Disaster resiliency: Interdisciplinary perspectives*, ed. N. Kapucu, C. V. Hawkins, and F. I. Rivera, 48–60. New York, NY: Routledge.

Rose, A., G. Oladosu, B. Lee, and G. B. Asay. 2009. The economic impacts of the September 11 terrorist attacks: A computable general equilibrium analysis. *Peace Economics, Peace Science and Public Policy* 15(2): Article 4. doi:10.2202/1554–8597.1161.

Rose, A., G. Oladosu, and S.-Y. Liao. 2007. Business interruption impacts of a terrorist attack on the electric power system of Los Angeles: Customer resilience to a total blackout. *Risk Analysis* 27(3):513–31. doi:10.1111/j.1539-6924.2007.00912.x

Ross, A. D. 2013. *Local disaster resilience: Administrative and political perspectives*. New York, NY: Routledge.

Ruth, M., and M. E. Ibarrarán. 2009. *Distributional impacts of climate change and disasters: Concepts and cases*. Northampton, MA: Edward Elgar.

Schapley, P., and L. Schwartz. 2014. Coastal hazard mitigation in Florida. In *Crisis and emergency management: Theory and practice*, ed. A. Farazmand 771–89. Boca Raton, FL: CRC Press.

Spatial Hazard Events and Losses Database for the United States (SHELDUS). 2010. Metadata. http://hvri.geog.sc.edu/SHELDUS (accessed December 25, 2010).

Strobl, E. 2011. The economic growth impact of hurricanes: Evidence from U.S. coastal countries. *Review of Economics and Statistics* 93(2):575–89. doi:10.1162/rest_a_00082

Studenmund, A. H. 2006. *Using econometrics: A practical guide*. New York, NY: Addison-Wesley.

Toya, H., and M. Skidmore. 2007. Economic development and the impacts of natural disasters. *Economics Letters* 94:20–25. doi:10.1016/j.econlet.2006.06.020

Turnbull, M., C. L. Sterrett, and A. Hilleboe. 2013. *Toward resilience: A guide to disaster risk reduction and climate change adaptation*, Warwickshire, UK: Practical Action Publishing.

UN International Strategy for Disaster Reduction. 2013. The hidden risks of economic globalization. In *From shared risk to shared value: The business case for disaster risk reduction, Global assessment report on disaster risk reduction*, 41–50. Geneva, Switzerland: United Nations Office for Disaster Risk Reduction.

U.S. Census Bureau (USCB). 2013. Topics. http://www.census.gov/topics.html (accessed March 15, 2013).

U.S. Census Bureau. 2014. U.S. county business patterns. http://www.census.gov/econ/cbp/index.html (accessed August 12, 2014).

U.S. Department of Agriculture Economic Research Service (USDA ERS). 2012. Data. http://ers.usda.gov/data-products.aspx (accessed May 20, 2012).

Waugh, W. L., and C. Y. Liu. 2014. Disasters, the whole community, and development as capacity building. In *Disaster and development: Examining global issues and cases*, ed. N. Kapucu and K. T. Liou, 167–79. Cham, Switzerland: Springer.

Wilson, G. A. 2012. *Community resilience and environmental transitions*. New York, NY: Routledge.

Wisner, B., J. C. Gaillard, and I. Kelmar. 2012. *The Routledge handbook of hazards and disaster risk reduction*. New York, NY: Taylor & Francis.

Zhou, H., J. Wang, J. Wan, and H. Jia. 2010. Resilience to natural hazards: A geographic perspective. *Natural Hazards* 53:21–41. doi:10.1007/s11069-009-9407-y