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Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma

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Abstract
Large-scale damage to the power infrastructure from hurricanes and high-wind events can have devastating ripple effects on infrastructure, the broader economy, households, communities, and regions. Using Hurricane Irma's impact on Florida as a case study, we examined: (1) differences in electric power outages and restoration rates between urban and rural counties; (2) the duration of electric power outages in counties exposed to tropical storm force winds versus hurricane Category 1 force winds; and (3) the relationship between the duration of power outage and socioeconomic vulnerability. We used power outage data for the period September 9, 2017–September 29, 2017. At the peak of the power outages following Hurricane Irma, over 36% of all accounts in Florida were without electricity. We found that the rural counties, predominantly served by rural electric cooperatives and municipally owned utilities, experienced longer power outages and much slower and uneven restoration times. Results of three spatial lag models show that large percentages of customers served by rural electric cooperatives and municipally owned utilities were a strong predictor of the duration of extended power outages. There was also a strong positive association across all three models between power outage duration and urban/rural county designation. Finally, there is positive spatial dependence between power outages and several social vulnerability indicators. Three socioeconomic variables found to be statistically significant highlight three different aspects of vulnerability to power outages: minority groups, population with sensory, physical and mental disability, and economic vulnerability expressed as unemployment rate. The findings from our study have broader planning and policy relevance beyond our case study area, and highlight the need for additional research to deepen our understanding of how power restoration after hurricanes contributes to and is impacted by the socioeconomic vulnerabilities of communities.

Keywords Hurricane Irma · Power outages · Restoration curves · Spatial lag models · Socioeconomic vulnerability · Electric utilities

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1 Introduction

One of the most disruptive effects of hurricanes occurs in the form of blackouts and electrical power outages. In 2017, Hurricane Maria devastated the US territory of Puerto Rico, causing the largest power outage in US history (Miller et al. 2018). Power outages have well-known economic impacts on the operation of flood control pumps and structures, wastewater treatment and distribution systems and pumping stations; lead to the degradation of communication capabilities; can shut down of oil and natural gas production and transportation; and, can lead to the shutdown of airports and ports with debilitating impacts on the provision of emergency supplies and humanitarian aid (Han et al. 2009; Hasan and Foliente 2015; FEMA 2017; Zimmerman et al. 2017; Miller et al. 2018; Mitsova et al. 2018). All of these events may lead to secondary impacts on schools, government institutions, medical facilities, and life-support health equipment.

To date, scholarship on hurricanes and power outages has focused on the pre-positioning of resources by utility companies prior to a disaster, as well as optimization of the restoration process. For example, several scholars have developed approaches to predict and forecast duration of power outages in the event of a hurricane, and to assess spatial patterns and characteristics of power outage risk (Han et al. 2009; Guikema et al. 2010; Nateghi et al. 2011; McRoberts et al. 2016; Tonn et al. 2016).

While extant scholarship on power outages has contributed greatly to understandings of power outage risk and measurement, this paper fills a crucial gap in our understanding the relationship between the duration of power outage and socioeconomic vulnerability. Using Hurricane Irma's impact on Florida as a case study, we examined: (1) differences in electric power outages and restoration rates between urban and rural counties; (2) the duration of electric power outages in counties exposed to tropical storm force winds versus hurricane Category 1 force winds; and (3) the relationship between the duration of power outage and socioeconomic vulnerability as a means to assessing gaps in service.

The paper begins with a brief overview of scholarship and research on methods used to predict temporal and spatial components of electric power outage from hurricanes and the impacts on vulnerable segments of the population, including medically fragile persons. This is followed by a study area section which includes information on Hurricane Irma in the state of Florida, as well as power outage and restoration rates by utility service provider type. The next two sections present the data, methods, and models in our analysis of power outage duration and restoration in our study area. The concluding section presents a summary of insights and findings, potential practical and policy implications, and research limitations.

2 Prediction and forecasting and applicability for utility companies

Zimmerman (2016) studied sixteen storms—eight during the period 1965–2003 and eight during the period 2003–2013—and found that power outage duration ranged from 1 h to 14 days, and 2 h to 27 days, respectively. Despite the high variability in the duration of electric power outages, a clustering in the range of a few hours to 3 days has been reported by Zimmerman et al. (2017). What is clear from these studies is the importance of forecasting such duration periods for pre- and post-disaster planning purposes.

The implications for pre-hurricane planning have also been noted by several scholars who have advanced approaches to predicting and forecasting duration of power outages and spatial patterns and characteristics of power outage risk (Han et al. 2009; Guikema et al. 2010; Nateghi et al. 2011; McRoberts et al. 2016; Tonn et al. 2016). For example, Nateghi et al. (2011) compared statistical methods for modeling power outage durations during hurricanes and examined the predictive accuracy of these methods. Wind speed is a common and important input variable in these models. McRoberts et al. (2016) updated a previously developed spatially generalized hurricane outage prediction model (SGHOPM) using a more comprehensive set of variables (including population, wind gust, wind duration, precipitation, soil moisture, tree characteristics, elevation, land cover, root zone depth) to predict the occurrence and number of outages for hurricanes and other high-wind events for census tracts in the southeastern USA. Tonn et al. (2016) used data on wind, rainfall and storm surge to assess which factors contribute to the risk of power outages in hurricanes. They found that storm surge did not emerge as an important predictor of power outage during hurricane Isaac.

Han et al. (2009) highlighted the importance of the findings for large investor-owned utility companies. Their models were developed using power outage data for nine hurricanes in three states served by a large, investor-owned utility company in the Gulf Coast region. The scholars also noted that the models can be used to examine a number of potentially “worst-case” scenarios (i.e., past or hypothetical strong hurricanes) and an assumed track (Han et al. 2009, p. 209).

3 Socioeconomic vulnerabilities

In addition to understanding the effects of physical characteristics and vulnerabilities that have been analyzed in past studies (Han et al. 2009; Guikema et al. 2010; Nateghi et al. 2011; McRoberts et al. 2016; Tonn et al. 2016), it is important to examine if and how socioeconomic vulnerabilities are affected by power outages and restoration.

Disaster vulnerability and resilience research has largely focused on urbanized areas given the potential for large-scale damage to complex interdependent infrastructure and impacts to diverse populations and various economic sectors. Understanding the fabric of rural places is important in terms of capabilities and resource for pre- and post-disaster planning (Cutter et al. 2016, p. 1250), including recovery of critical infrastructure systems.

Low-income communities may be particularly vulnerable in power outage situations after disasters. The authors focused on Hispanic/Latinos, the fastest growing population group in New Jersey, and highlighted the vulnerability of low-income, minority-dominated communities to prolonged loss of electricity from hurricane Sandy (Burger et al. 2017, p. 323). The potential for cascading impacts of power outages on emergency medical services has also been documented by other scholars (Beatty et al. 2006; Huang et al. 2014; Klinger et al. 2014; Kraushar and Rosenberg 2015; Burger et al. 2017; FEMA 2017; Mitsova et al. 2018). Home-bound medically fragile and chronically ill high-risk individuals are unable to self-relocate during a mass power outage because of their reliance on power-dependent durable medical equipment (FEMA 2017).

Further work is needed focusing on the relationship between potentially vulnerable communities (e.g., population on public assistance; population with sensory, physical and mental disability) and power outages, in order to provide insights into resource provision and allocation of critical emergency services in time of disaster, and for crafting appropriate preventative and mitigation strategies. Other traditional socioeconomic and demographic vulnerability and risk factors post-disaster include poverty, age (i.e., children, elderly), female gender, housing tenancy, minority racial status, and educational attainment

(Cutter et al. 2003; Laska and Morrow 2006; Cutter et al. 2010; Peacock and Girard 1997; Esnard et al. 2011; Peacock et al. 2012; Lai et al. 2017).

According to Burger et al. (2017, p. 316), minority, low-income, and older individuals are more vulnerable to serious health impacts compared to others. In a study of Red Hook in Brooklyn after hurricane Sandy in 2012, Kraushar and Rosenberg (2015) reported that local ambulatory medical services including clinics, pharmacies, home health agencies, and other resources were severely damaged. They also highlight significant gaps in mitigation and response systems to address medical needs in low-income urban communities during a crisis (Kraushar and Rosenberg 2015).

4 Case study: Hurricane Irma and state of Florida

The state of Florida has seen its fair share of hurricanes and their devastating impacts. In 1992, Hurricane Andrew caused 44% (1.4 million) of Florida Power and Light Company's customers to lose power (Larsen et al. 1996). More than 6 million Floridians lost power due to Hurricane Wilma in 2005 and some were left without power for days. The cascading impacts of power outages also affected the availability of other supplies and long lines formed at gas stations and grocery stores for fuel and water (Miller 2016).

After battering the northern Caribbean islands, Hurricane Irma made landfall on September 10, 2017, in the Florida Keys as a Category 4 hurricane and then struck southwestern Florida at Category 3 intensity. It was one of the strongest and costliest hurricanes on record in the Atlantic basin and caused widespread devastation in Florida. Along with high winds, Irma produced heavy rain across much of the state of Florida. While the maximum rainfall was reported in Ft. Pierce, Florida, in St. Lucie County, where 21.66 inches of rain was measured between 9 and 12 September, heavy rainfall caused flooding of streets and low-lying areas across much of the Florida peninsula. There was major flooding along the St. John's River at many locations including the Jacksonville metropolitan area, where hundreds of people were rescued. Power outages were the most widespread and severe in the Keys, where most homes were badly damaged or destroyed, and there was extensive tree damage throughout the island chain. About 6 million residents in Florida were evacuated from coastal areas (Cangialosi et al. 2018, p. 13).

4.1 Counties of interest

Hurricane Irma's tropical storm force wind swath (34 knots; 39–73 mph) covered the entire state of Florida and provides a good approximation of the region impacted by the hurricane and our choice of study area. There are 67 counties in the State of Florida. During Irma, there was a subset of 20 counties impacted by Category 1 hurricane-force winds (64 knots; 74–95 mph), as shown in Fig. 1.

4.2 Urban and rural county classification

There are several approaches for designating urban and rural counties. Florida statute 381.0406 related to rural health networks define rural areas as places with population density of 100 persons or less per square mile. Cutter et al. (2016) used the USDA rural–urban continuum codes to differentiate rural and urban places; those continuum codes place counties in nine categories based on population size. We use the 2013 NCHS a six-

Fig. 1 Counties in Hurricane Irma's path and 64 knot wind swath

level urban–rural classification scheme[1] for US counties and county-equivalent entities, which is based on the Office of Management and Budget's (OMB) February 2013 delineation of metropolitan statistical areas (MSA) and micropolitan statistical areas (https://www.cdc.gov/nchs/data_access/urban_rural.htm). For purposes of our analysis, we grouped classifications 1–4 as urban, and classifications 5–6 as rural. See Fig. 2 for a spatial depiction of Florida's urban–rural landscape.

[1] The six-level urban–rural classification scheme:

1. Large central metro counties in MSA of 1 million population that: (1) contain the entire population of the largest principal city of the MSA, or (2) are completely contained within the largest principal city of the MSA, or (3) contain at least 250,000 residents of any principal city in the MSA.
2. Large fringe metro counties in MSA of 1 million or more population that do not qualify as large central.
3. Medium metro counties in MSA of 250,000–999,999 population.
4. Small metro counties are counties in MSAs of less than 250,000 population.
5. Nonmetropolitan counties: Micropolitan counties in micropolitan statistical area.
6. Noncore counties not in micropolitan statistical areas.

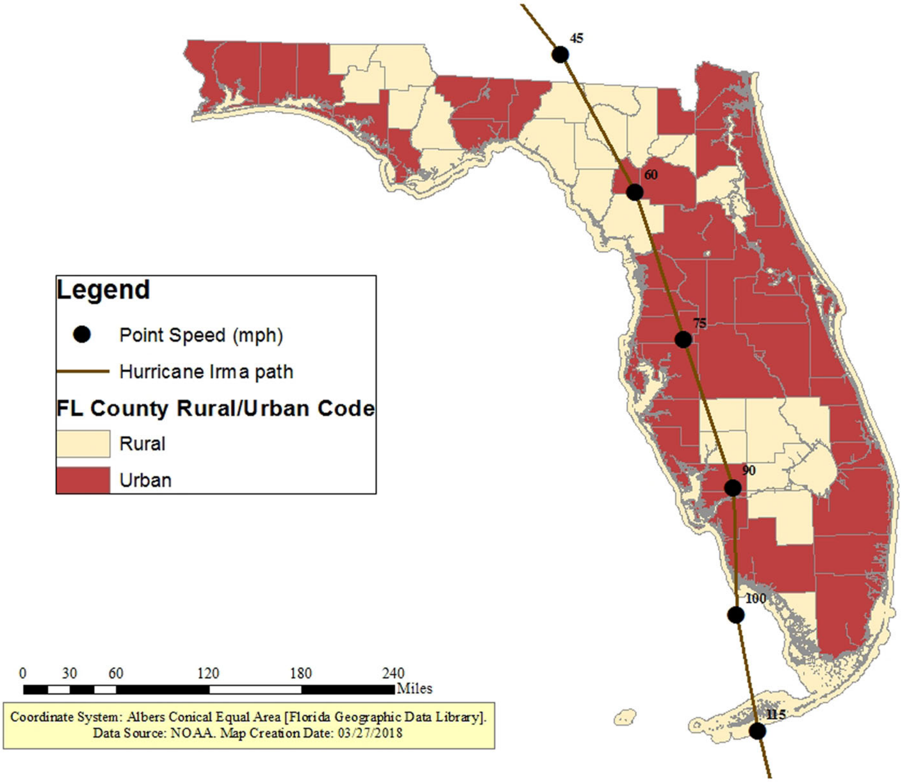


Fig. 2 Urban–rural classification of Florida counties

4.3 Types of utility companies: electric power service provision

Electrical power provision and post-disaster stabilization, restoration, and reestablishment of facility operations remain within the purview of the utility companies (FEMA 2017). According to the Florida Public Service Commission (2017), three types of utility service providers (defined below) serve residential, commercial, and industrial sectors in our study area:

- Investor-owned electric utilities—Florida Power and Light, Tampa Electric, Gulf Power, Florida Public Utility Cooperation, Duke Energy). According to FEMA (2017, pp. 4–5), investor-owned utilities are operated as private, taxpaying businesses whose management is not associated with any government agency (FEMA 2017).
- Municipal Electric Utilities, also known as public power utilities are not-for-profit utilities owned and operated by state or local governments or by agencies, authorities, or instrumentalities of such governments (FEMA 2017, pp. 4–5).
- Rural Electric Cooperatives are private, independent, not-for-profit electric utilities owned by the customers they serve, and tend to provide service in rural areas that are not served by other utilities (FEMA 2017, pp. 4–5).

5 Data and methods

We used two main datasets to generate electric power restoration curves and for statistical modeling. Spatial analysis and mapping were facilitated using ArcGIS version 10.5. Hurricane Irma track and wind swath data layers downloaded from the National Hurricane Center GIS Archive[2] are reprojected to Albers Conical Equal Area to match that of the county boundaries and hospitals datasets downloaded from the Florida Geographic Data Library (FGDL).

5.1 Power outage data

The power outage data are available for period September 9, 2017–September 29, 2017, and organized by short-time intervals and by utility service provider. We used the 6 a.m. snapshot data across the 21-day period of study. This 6 a.m. morning time was chosen as a good indicator of whether a household would be able to start their day with power in the house. The data obtained from the Florida Division of Emergency Management[3] allow us to capture the following variables at the state and county levels:

- Statewide:
    - Percentage of accounts without power (see Fig. 3).
- Countywide:
    - County name;
    - Urban/rural classification;
    - Total number of accounts;
    - Percent accounts Investor-Owned Electric Utilities;
    - Percent accounts Rural Electric Cooperatives;
    - Percent accounts Municipal Electric Utilities;
    - Percent total customers without power;
    - Percent Investor-Owned Utilities without power;
    - Percent Rural Electric Cooperatives without power;
    - Percent Municipal Electric Utilities without power.

5.2 Socioeconomic variables

Given that Hurricane Irma made landfall in 2017, we used the 2016 5-year American Community Survey (ACS)[4] data to compile the following six broad categories of demographic and socioeconomic variables:

- Race/Ethnicity (% population White; % population Latino; % population African American; % population Asian; % population American Indian; % population other);
- General population profile: total population, population density;

[2] https://www.nhc.noaa.gov/gis/archive_besttrack_results.php?id=al11&year=2017&name=Hurricane%20IRMA.

[3] http://archive.floridadisaster.org/info/outage_reports/irma/.

[4] The 2012-2016 ACS 5-year estimates are based on data collected from January 1, 2012 to December 31, 2016, released by the US Census Bureau on December 7, 2017 (https://www.census.gov/programs-surveys/acs/news/data-releases/2016/release.html).

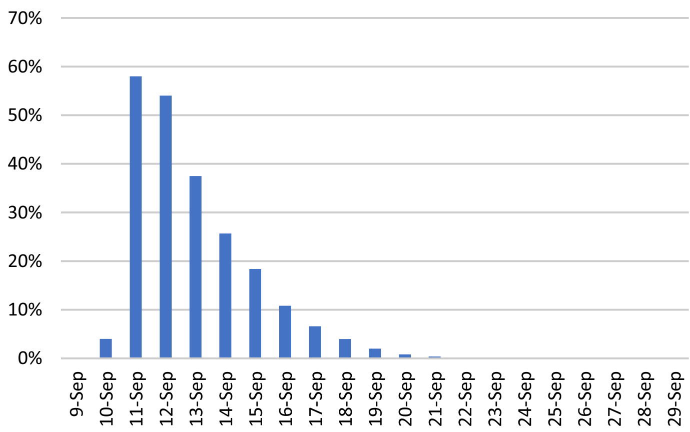


Fig. 3 Percent accounts without power for Florida (9/9–9/29). *Source*: Hurricane Irma power outage data, Florida Division of Emergency Management

- Dependence: % population less than 5 years; % population older than 65 years; % population without a vehicle; % population on public assistance; % limited English speaking households; % population with sensory, physical and mental disability; % population without health insurance;
- Housing and households: % renter occupied housing; % HHs using over 30% of income for housing; % single person HHs over age 65;
- Educational attainment: % population with less than a high school education;
- Income and poverty: unemployment rate; % living below the poverty level; % HHs using over 30% of income for housing.

5.3 Restoration curves

Loss of service and the timelines of restoration/repair/replacement after a disaster can be represented as a function of time (Dong et al. 2004, p. 11). A restoration curve typically represents the level of the power system performance within a specific period of time (usually in days) from the point of maximum loss in functionality to the point of regaining full performance and pre-disaster level of service (Dong et al. 2004).

Using power outage data for the State of Florida at a county level, we derive and compare restoration curves for (a) urban and rural counties within the hurricane-force wind swath and (b) urban and rural counties within the tropical cyclone wind swath. The integration of restoration curves with additional data enables evaluation of the performance of power systems and the consequences of system interruptions caused by hurricanes for various types of providers from large utility networks to rural electric cooperatives and municipally owned utility companies. The analysis provides critical information on the speed of restoration taking into account the structural and social dimensions of the community recovery process.

5.4 Statistical modeling

In specifying the statistical modeling approach, several methodological issues emerged pertaining to the identification of potential predictor variables that suggested the possibility of local disruptions being spatially correlated with understudied local characteristics beyond physical damage to substations and the power distribution network. To address these methodological issues, we focused on spatial autoregressive models to study regional effects and spatial interdependence of observed power outages, considering the importance of spatial dependence in the dependent variable and error term (also known as spatial autocorrelation) (Anselin 1988). Spatial dependence occurs when values observed at different locations are autocorrelated, that is, values observed in one location influence the values observed in neighboring locations (Peeters and Chasco 2006). Non-spatial regression models that do not account for spatial autocorrelation typically violate two critical assumptions of the regression modeling technique, notably, independence of the residuals and homoscedasticity.

5.4.1 Data and variables

Using the power outage duration as the dependent variable, we seek to assess the effects of hurricane-force wind, outage characteristics, provider characteristics, urban/rural dichotomy, and socioeconomic factors. Duration of the power outage expressed as the average number of days without electricity at a county level has been selected as the dependent variable. The independent variables used in the models' specification are grouped into the following five categories (see Table 1 for descriptive statistics).

1. Wind swath
   - A dichotomous variable indicating the counties having their centroid within the hurricane-force wind swath and counties within the tropical storm wind swath (variable wind swath).
2. Outage and restoration characteristics
   - Severity expressed as the percent customers without electricity at a county level during the first 48 h immediately after landfall (9/11/17 and 9/12/17). See Fig. 4a, b for the spatial pattern of power outages.
   - Speed of restoration (% customers without electricity) one week after landfall (9/17/17). The cutoff date was selected based on the average duration of the power outages for Florida (7.2 days) in the aftermath of Hurricane Irma.
3. Provider characteristics
   - Percent customers served by rural and municipally owned utility cooperatives.
4. Urban/rural dichotomy
   - A dichotomous variable controlling for the effect of the urban/rural classification.
5. Social aspects of vulnerability to power outages; the choice of these variables is discussed in a later section.
   - Percent population Hispanic or Latino.
   - Unemployment rate.
   - Percent of population with sensory, physical and mental disability.

Table 1 Descriptive statistics of variables used in models

Variable	Min	Max	Mean	SD
% Served by rural and municipal cooperatives	0	100	44.24	33.22
% Outages on September 11, 2017	0	86	46.27	30.4
% Outages on September 12, 2017	0	99	52.06	27.41
% Outages on September 17, 2017	0	65	6.66	10.91
% Hispanic/Latino	71.1	66.67	13	12.96
% Disability	10.3	25	16.65	3.8
Unemployment rate	4.8	13.6	8.64	1.85
Urban/rural classification	0	1	N/A	N/A
Wind swath	34 knots	64 knots	N/A	N/A

Percentages are listed as percent by county

5.4.2 Model specification

Three spatial lag models were estimated using the average duration of the power outages by county as the dependent variable. Each model was intended to: (1) assess the effect of the type of power provider and hurricane wind on the duration of power outages; and (2) understand the relationship between socioeconomic vulnerability and the duration of power outages.

For each model, ordinary least squares (OLS) estimates are first obtained and the presence of spatial autocorrelation is assessed by obtaining the Lagrange multiplier (LM) and the robust Lagrange multiplier (RLM) test statistics for error and lag dependence (Anselin 1988; Anselin et al. 1996). A linear model with autoregressive errors includes a spatial autoregressive coefficient ρ (rho), and spatially lagged dependent variable. Spatial weighting matrices are estimated to derive spatial lags and autoregressive terms. Spatial weights can be distance based (e.g., inverse distance weighting) or estimated from kernel functions (Anselin 2002; Peeters and Chasco 2006; Anselin and Lozano-Garcia 2008; He and Lin 2015). Adaptive kernels have adjustable bandwidths with narrow bands in areas with higher density of data points and wider bands in areas with low density of data points (Peeters and Chasco 2006). In this study, we employ the heteroscedastic and autocorrelation robust (HAC) algorithm (Kelejian and Prucha 2007) using an adaptive bandwidth kernel parameter with a Gaussian distribution.

6 Findings

The spatial extent and duration of the power outages in Florida following Hurricane Irma provide the basis for understanding the restoration time of large utility networks and local providers. The spatial autoregressive models allow us to examine the disruptions of the power supply provided by rural electric cooperatives and municipally owned utilities in terms of duration and exposure to hurricane-force winds, and to better understand if extended power outages disproportionately affect vulnerable populations following a hurricane landfall.

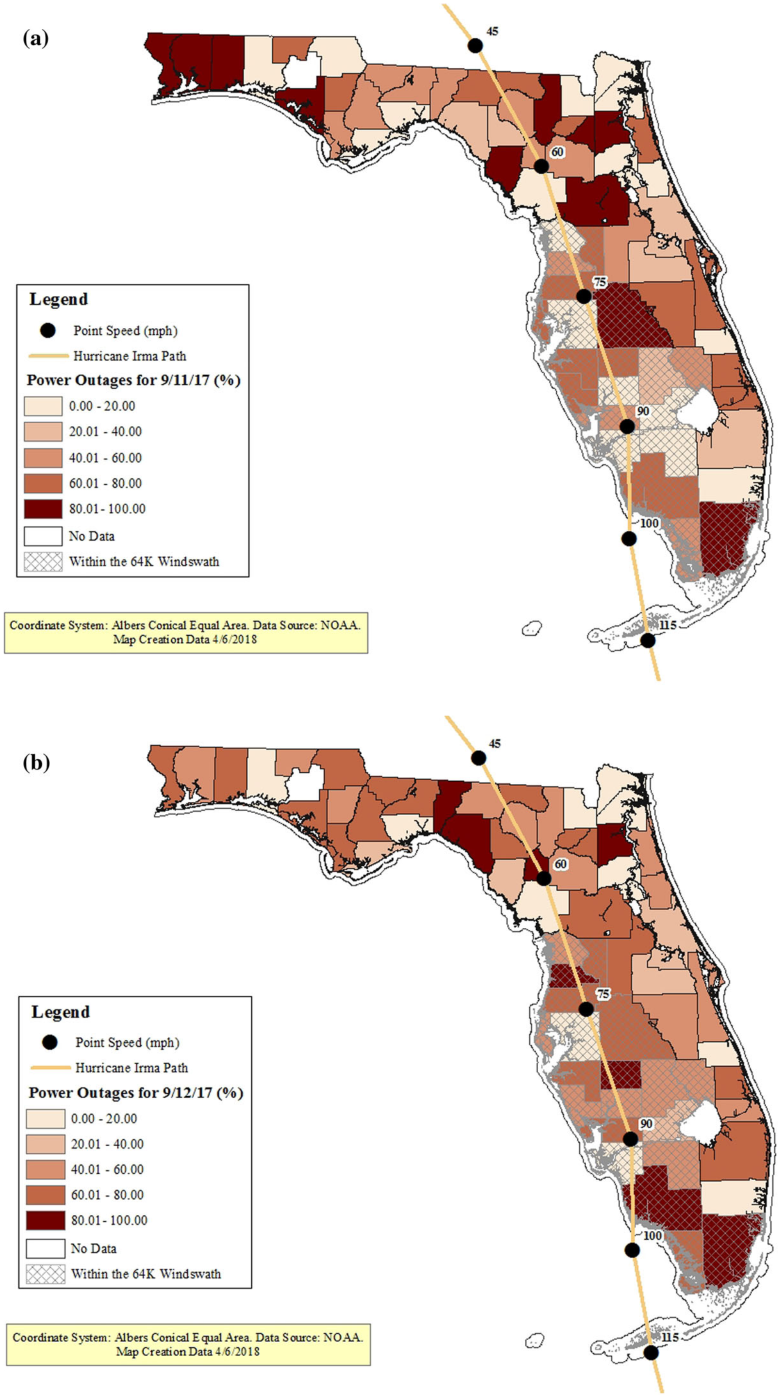
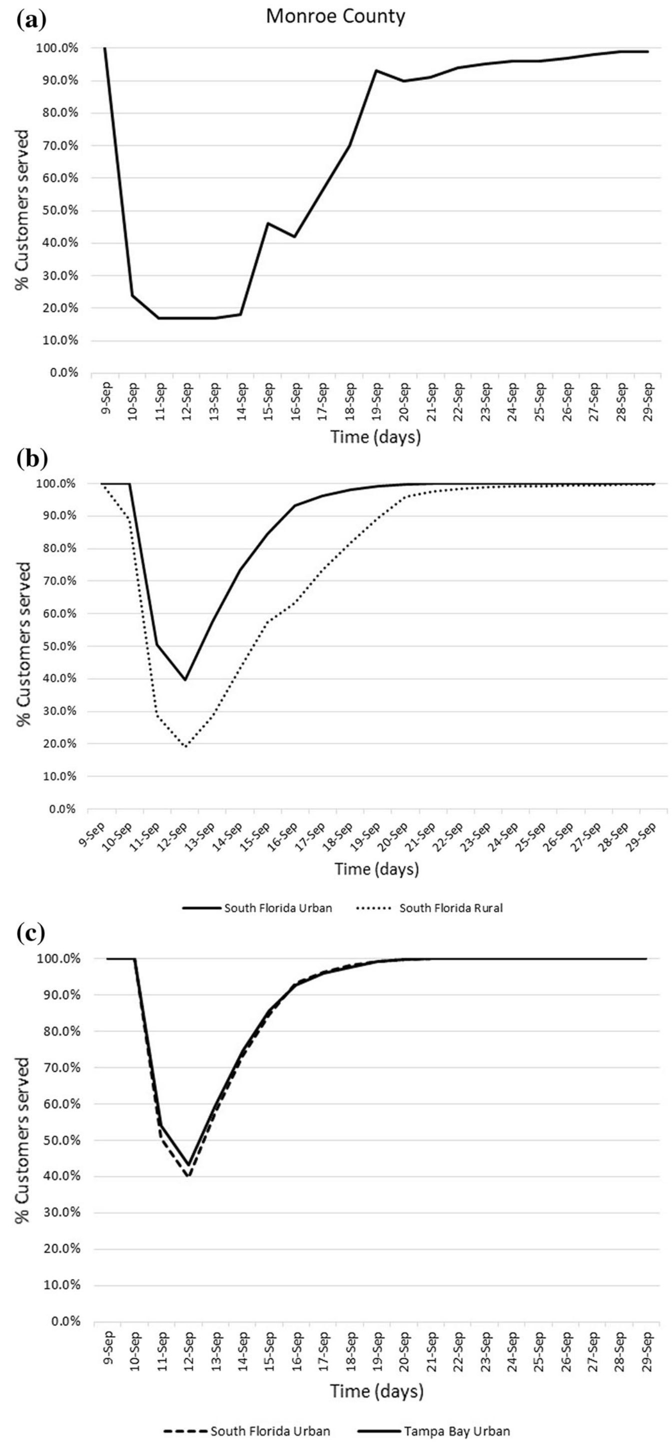


Fig. 4 Percent customers without power on **a** September 11, 2017, in Florida counties. **b** September 12, 2017, in Florida counties


(a)
Monroe County
% Customers served
Time (days)
(b)
% Customers served
Time (days)
South Florida Urban
South Florida Rural
(c)
% Customers served
Time (days)
South Florida Urban
Tampa Bay Urban

◀ **Fig. 5** **a** Restoration of power supply as a function of time for Monroe County (the Florida Keys) within the Category 1 hurricane wind swath (74–95 mph or 120–153 km/h wind speed). **b** Restoration of power supply as a function of time for urban and rural counties in South Florida within the Category 1 hurricane wind swath (74–95 mph or 120–153 km/h wind speed). **c** Restoration of power supply as a function of time for urban counties in South Florida and the Tampa Bay regions within the Category 1 hurricane wind swath (74–95 mph or 120–153 km/h wind speed)

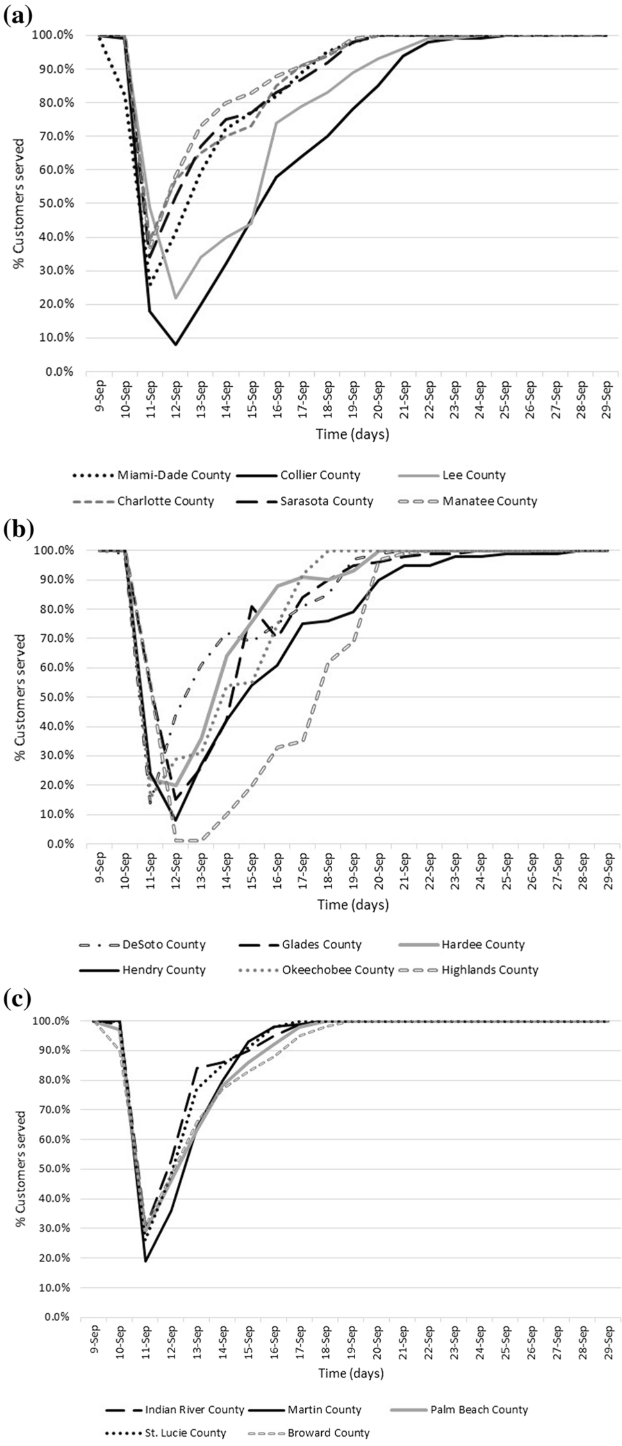
6.1 Restoration curves

At the peak of the power blackout following Hurricane Irma, over 36% of all accounts in Florida were without electricity. The descriptive statistics indicate that the average number of days without electricity in the State of Florida following Hurricane Irma was 7.2 days. Monroe County had the longest reported duration of power outages of 20 days (Fig. 5a). Figure 5a–c displays the restoration curves for 13 counties in South Florida that were in the direct path of Irma as the hurricane first made a landfall in Cudjoe Key in Monroe County, and a second landfall near Marco Island in Collier County, where sustained winds reached over 100 mph (160 km/h). In Monroe County, where 99% of the electric power is provided by rural electric cooperatives and municipally owned utility companies, nearly 85% of customers lost power and the restoration process did not begin until the search and rescue missions were completed and the main roads were cleared of debris. Within 10 days after the landfall, the power was restored to over 90% of the customers despite fluctuations during September 15–16 and September 19–20 time periods.

To understand the various factors that contribute to differences in power outage duration at a county level, we first compare the restoration curves for urban and rural counties within the hurricane-force wind swath (64 knots). Figure 5b displays the cumulative restoration curves between the urban counties (i.e., Miami-Dade, Collier, Lee, Charlotte, Sarasota, and Manatee) and rural counties (i.e., DeSoto, Glades, Hardee, Hendry, Okeechobee, and Highlands) in South Florida. The results clearly indicate a considerably longer power outage duration and a slower restoration process in the rural counties. To further understand if there are systematic differences in the power restoration process, we compare the cumulative power restoration curves for the urban counties in South Florida and the Tampa Bay region. As Fig. 5c indicates, the power restoration process in both regions follows an almost identical trajectory.

Figure 6a displays the restoration curves for six urban counties in South Florida on the path of Irma. The restoration curves for Miami-Dade, Charlotte, Sarasota, and Manatee counties show a faster process of power restoration compared to Collier and Lee counties. However, the six rural counties in South Florida experienced longer power outages and, as Fig. 6b indicates, much slower and uneven restoration. The rural counties have much higher proportion of their electricity delivered by rural electric cooperatives and municipally owned utilities (as high as 77% in Hardee County and nearly 50% in Glades and Hendry). Figure 6c shows the restoration curves for Indian River, St. Lucie, Martin, Palm Beach, and Broward counties which remained in the tropical storm wind swath. The curves indicate a considerable loss of power in all five counties with the higher number of reported outages in Martin County. The restoration curves in these five counties are similar and indicate much faster restoration compared to the adjacent rural counties.

More than 20 counties within the tropical storm wind swath also experienced extended power outages. The outages were particularly severe in several rural counties in the northern central part of Florida. Ten rural counties in this area experienced a power outage of 7–8 days. On average, 65.5% of the electricity in these areas is provided by cooperatives


(a)
% Customers served
Time (days)
Miami-Dade County
Collier County
Lee County
Charlotte County
Sarasota County
Manatee County
(b)
% Customers served
Time (days)
DeSoto County
Glades County
Hardee County
Hendry County
Okeechobee County
Highlands County
(c)
% Customers served
Time (days)
Indian River County
Martin County
Palm Beach County
St. Lucie County
Broward County

◀**Fig. 6** **a** Restoration of power supply as a function of time for Miami-Dade, Collier, Lee, Charlotte, Sarasota, and Manatee counties in South Florida within the Category 1 hurricane wind swath (74–95 mph or 120–153 km/h wind speed). **b** Restoration of power supply as a function of time for DeSoto, Glades, Hardee, Hendry, Okeechobee and Highlands counties in South Florida within the Category 1 hurricane wind swath (74–95 mph or 120–153 km/h wind speed). **c** Restoration of power supply as a function of time for Indian River, Martin, Palm Beach, St. Lucie and Broward counties in southeast Florida within the tropical storm wind swath (39–73 mph or 63–119 km/h wind speed)

and municipally owned utility companies. The four urban counties in the region exhibited similar patterns of outage duration and speed of restoration. Nearly 64% of the customers in these four counties are served by local electricity providers.

6.2 Statistical analysis

Ordinary least squares estimates were first obtained with model diagnostics for spatial dependence. The F-statistics of 49.84 (p value < 0.0001) indicate a good model fit with an R^2 of 0.8034. The regression coefficients of the percent customers served by rural and municipally owned cooperatives, urban/rural classification, as well as percent power outages within 48 h and a week from Irma's landfall are found to be statistically significant and of the expected sign. The multicollinearity condition number of 8.876 is below 30 which indicates that collinearity is not an issue with this model. The Lagrange multiplier (LM) and robust Lagrange multiplier (RLM) test statistics indicate positive residual spatial autocorrelation providing evidence that a spatial lag model is appropriate for the data. We estimated three spatial lag models to deepen our understanding of: (1) the differences in electric power outages and restoration rates between urban and rural counties; (2) the duration of electric power outages in counties exposed to tropical storm force winds versus hurricane Category 1 force winds; and (3) the relationship between the duration of power outage and socioeconomic vulnerability as a means to assessing gaps in service. Table 2 provides a summary of the three models.

In Model 1, the coefficients for all explanatory variables are statistically significant at $\alpha = 0.05$ with the exception of the autoregressive coefficient *rho* which is significant at $\alpha = 0.10$. The spatial pseudo R^2 for this model is 0.821. In Model 2, the imapct of wind force on power outage duration (i.e., wind swath) was also included as a covariate. The results indicate that wind swath has a positive effect on the duration of the power outages, but this relationship is weaker compared to the effect of the percent customers served by rural and municipally owned cooperatives. The spatial pseudo R^2 for this model is 0.7730.

In Model 3, the final selection of the covariates included in the model was preceded by an evaluation of several socioeconomic variables including percent African Americans; percent of the population without a vehicle; percent of the population on public assistance; percent households speaking limited English; percent living below the poverty level; and percent of the households using over 30% of their income for housing, unemployment rate, and percent of the population with a disability status. In order to select the appropriate predictor variables, we conducted correlation and principal component analysis (PCI). The PCI analysis yielded two well-defined components. The first component included housing and income characteristics, while the second encompassed poverty, disability, and public assistance recipients. Based on these results, we constructed two indicators for inclusion in the statistical models. The indicators, which explained 60.8% of the variance in the PCI analysis, were not found to be significant. Percent living below the poverty level, % population African American; % population without a vehicle; % population on public assistance; % limited English speaking households; and the percent of households using

Table 2 Models 1–3 results

Variable	Model 1			Model 2			Model 3		
	Coef.	SE	Std. Coef.	Coef.	SE	Std. Coef.	Coef.	SE	Std. Coef.
% Served by rural and municipal cooperatives	0.019	0.007	2.596***	0.024	0.008	2.893***	0.226	0.007	3.574***
% Outages on September 11, 2017	0.035	0.011	3.103***	0.061	0.013	4.677***	0.066	0.009	7.389***
% Outages on September 12, 2017	0.053	0.011	4.727***						
% Outages on September 17, 2017	0.126	0.053	2.368**	0.144	0.046	3.129***	0.154	0.024	6.371***
% Hispanic/Latino							0.069	0.025	2.780***
% Disability							0.207	0.091	2.284**
Unemployment rate							− 0.248	0.148	− 1.671*
Urban/rural classification	1.444	0.373	3.872***	1.071	0.461	2.325**	1.4	0.612	2.289**
Wind swath				0.852	0.505	1.688*			
Spatial autoregressive parameter (denoted by rho)	0.178	0.097	1.835*	0.206	0.123	1.678*	0.147	0.081	1.812*
		Model 1			Model 2			Model 3	
Spatial pseudo R^2		0.821			0.773			0.795	

***$p < 0.001$; **$p < 0.05$; *$p < 0.1$

over 30% of their income for housing, when considered as separate predictor variables, were also found to be nonsignificant. These variables were not given further consideration in specifying the final models.

Model 3 examines the combined effects of both physical exposure (wind swath), type of electricity provider (% rural and municipal cooperatives), severity of the impact expressed as the percentage of people without power immediately after landfall, the speed of restoration expressed as the percentage of people without power a week after landfall, and socioeconomic vulnerability. The diagnostic tests for spatial dependence indicate that a spatial lag model with a spatially lagged dependent variable and a spatial autoregressive coefficient provides a good fit to the data. In Model 3, the regression coefficients for the percent served by rural and municipal cooperatives, percent outages on September 11, 2017, percent outages on September 17, 2017, and the effect of the urban/rural classification are statistically significant at $\alpha = 0.05$. The coefficient for the percent Hispanic or Latino populations was found to be highly significant (p value = 0.005). We also found that the coefficient for the percent of the population with sensory, physical and mental disability was also significant at $\alpha = 0.05$. The spatial autoregressive coefficient and unemployment rate were found to be significant at $\alpha = 0.10$. One unexpected result was the negative sign of the coefficient for the employment rate. One possible explanation is the relatively weak inverse correlation between unemployment rate and urban/rural classification (− 0.5, p value < 0.001). The Pearson correlation of 0.4 between unemployment rate and disability shows weak positive correlation. The correlation coefficient for percent Hispanic and Latino populations and unemployment rate equals 0.02 (i.e., virtually no correlation). Similarly, the correlation coefficient between percent Hispanic and Latino population and percent of the population with a disability status was not significant ($r = 0.04$, p value = 0.67). In comparison with Model 2, there was a slight improvement in the spatial pseudo R^2 in Model 3.

7 Discussion and conclusion

Electric power outages impact most sectors of society and cause disruptions to other infrastructure systems, households, the economy, school, emergency services, and critical services (such as hospitals) that depend on electricity. This is due to the critical interdependencies that exist between power, transportation, communication, water, and wastewater.

Overall, the results from all three statistical models indicate that the duration of power outages during Hurricane Irma can be explained by multiple factors. Importantly, the presence of a strong hurricane wind field is only one of these factors. The results consistently indicate a strong relationship between the duration of the power outages and the type of electricity provider. The results show that the percentage of customers served by cooperatives and municipally owned utilities is a strong predictor of the duration of extended power outages. This finding also indicates that cooperatives and municipally owned utilities may not have the economies of scale that investor-owned utilities have that allow the latter to pre-position staff and crew workers from other states to work on restoration after the event. Larger utilities also may have more resources that they can deploy to harden and fortify grid infrastructure. For instance, after hurricane Wilma in 2005, providers such as Florida Power and Light (FPL) and Duke Energy spent around \$2.4 billion to \$4 billion to fortify their grids and took various steps such as installing flood monitors in substations, smart meters, and intelligent devices, and investing in “selfhealing" systems that can detect, isolate, and reroute power when a problem occurs (Klas 2017). There is a strong positive association across all three models between duration and whether the disruptions occur in urban or rural areas, also corroborated by the restoration curves.

Finally, there is positive spatial dependence between power outages and several social vulnerability indicators. It is noteworthy that the three socioeconomic variables found to be statistically significant highlight three different aspects of vulnerability to power outages. The findings suggest that areas with higher percentages of Hispanic and Latino populations have experienced longer power outages in the wake of Hurricane Irma. We also found that longer duration of power outages was also positively associated with higher percentage of individuals with sensory, physical and mental disability. This finding is alarming since home-bound medically fragile and chronically ill often rely on power-dependent durable medical equipment which, when rendered inoperable, puts them at higher risk of deterioration of their medical condition (Burger et al. 2017; FEMA 2017).

Several limitations should be considered in evaluating the findings. The use of counties as the unit of analysis was driven by the available county-level power outage data. We acknowledge that there is a wide inter- and intra-county variation in population, population density, household composition, and urban/rural characteristics in the State of Florida. Beyond wind swaths, the intensity and size of the wind fields produced by tropical cyclones are known to trigger widespread power outages. As such, wind speed and other meteorological and environmental data can be used to further deepen our understanding of the factors that contribute to extended power outages (Guikema et al. 2010; Nateghi et al. 2011; Tonn et al. 2016). Additionally, although we focused on the tropical storm and Category 1 hurricane wind swaths, we acknowledge that interpretation of restoration times among counties in various parts of Florida should ideally consider that some counties began repair work ahead of others.

At the global level, the list of socioeconomic indicators has grown to include displaced populations, migrants, and returnees (IFRC 2016). Although beyond the scope of our studies, vulnerability assessments, in hazard-prone states such as Florida that also serve as a destination State for displaced persons, need to capture this vulnerable segment of the population. A case in point is the most recent exodus of Puerto Ricans who have found refuge in Florida after Hurricane Maria and whose vulnerabilities are compounded by housing and job insecurities, and language barriers. Percent of Hispanic/Latino persons in counties were significantly associated with average duration of power outages. Although a more thorough examination of demographic profiles of these communities can shed more light on this finding, this is useful information for utility companies, emergency managers, and disaster planners. As noted by Liévanos and Horne (2017), utility companies typically do not monitor or have knowledge about the link between outage duration and socioeconomic disadvantages. However, if utility providers can work with disaster planners and emergency managers to understand the linkages between socioeconomic vulnerabilities and power outages, they could take steps to implement programs that would account for spatial inequities and improving service to vulnerable populations, particularly the medically vulnerable. Such efforts could "improve energy justice (and) electrical grid resilience (Liévanos and Horne 2017, p. 209)," and lead to improved community recovery outcomes. One main challenge in countries like the USA is that critical infrastructure (such as electricity production facilities) is predominantly owned by the private sector and user cooperatives (Zimmerman and Farris 2010; Auerswald et al. 2005; Austin et al. 2015). The ownership of electrical power utilities by different stakeholders led Hasan and Foliente

(2015, p. 2145) to recommend a stakeholder-oriented lens to understand the values and limitations of methodologies used to assess the impact of extreme events on infrastructure.

Moving forward, pre-disaster preparation, post-disaster restoration, and disaster mitigation and adaptation strategies necessitate collaboration and partnerships within and between public, private, and nonprofit sectors. Murià-Vila et al. (2018) emphasized the need for collaboration between the Federal Electricity Commission (CFE) and other entities to ensure rapid mobilization, rapid restoration and minimize future damage and losses in their analysis of Hurricane Odile which left 95% of the inhabitants in Baja California Sur in Mexico without electricity. Furthermore, an increased awareness of both power grid vulnerability and socioeconomic vulnerabilities are required by utility providers, policy makers, politicians, emergency management professionals, energy experts and residents—the typology of stakeholders discussed by Hasan and Foliente (2015). The findings from our study have broader planning and policy relevance beyond our case study area and highlights that the need for additional research to deepen our understanding of how power restoration after hurricanes contributes to and is impacted by the socioeconomic vulnerabilities of communities.

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References

Anselin L (1988) Spatial econometrics: Methods and models. Kluwer, Dordrecht

Anselin L (2002) Under the hood: issues in the specification and interpretation of spatial regression models. Agric Econ 27(3):247–267

Anselin L, Lozano-Garcia N (2008) Errors in variables and spatial effects in hedonic house price models of ambient air quality. Empirical Economics 34(1):5–34

Anselin L, Bera A, Florax R, Yoon M (1996) Simple diagnostic tests for spatial dependence. Reg Sci Urban Econ 26:77–104

Auerswald P, Branscomb LM, La Porte TM, Michel-Kerjan E (2005) The challenge of protecting critical infrastructure. Issues Sci Technol 22(1):77–80

Austin RF, DiSera DP, Brooks TJ (2015) GIS for critical infrastructure protection. CRC Press, Boca Raton

Beatty ME, Phelps S, Rohner C, Weisfuse I (2006) Blackout of 2003: public health effects and emergency response. Public Health Rep 121:36–44

Burger B, Gochfeld M, Pittfield T, Jeitner C (2017) Responses of a vulnerable Hispanic population in New Jersey to Hurricane Sandy: access to care, medical needs, concerns, and ecological ratings. J Toxicol Environ Health Part A 80(6):315–325

Cangialosi JP, Latto AS, Berg R (2018) National hurricane center tropical cyclone report: Hurricane Irma 30 August–12 September 2017. National Oceanic and Atmospheric Administration and National Hurricane Center. Retrieved March 2018 from https://www.nhc.noaa.gov/data/tcr/AL112017_Irma.pdf

Cutter SL, Boruff B, Shirley W (2003) Social vulnerability to environmental hazards. Soc Sci Q 84(2):242–261

Cutter SL, Burton CG, Emrich CT (2010) Disaster resilience indicators for benchmarking baseline conditions. J Homel Secur Emerg Manag 7(1):1547–7355

Cutter SL, Ash KD, Emrich CT (2016) Urban–rural differences in disaster resilience. Ann Am As Geogr 106(6):1236–1252

Dong X, Shinozuka M, Chang S (2004) Utility power network systems. In: 13th world conference on earthquake engineering Vancouver, B.C., Canada August 1–6, 2004 Paper No. 527. http://www.iitk.ac.in/nicee/wcee/article/13_527.pdf. Accessed 27 March 2018

Esnard A-M, Sapat A, Mitsova D (2011) An index of relative displacement risk to hurricanes. Nat Hazards 59(2):833–859

FEMA (Federal Emergency Management Agency) (2017) Power outage incident annex to the response and recovery federal interagency operational plans: managing the cascading impacts from a long-term power outage. Retrieved March 2018 from https://www.fema.gov/media-library/assets/documents/154058

Florida Public Service Commission (2017) Facts and figures of the Florida utility industry. Office of Consumer Assistance and Outreach, Florida Public Service Commission, Tallahassee, FL. Retrieved March 2018 from http://www.psc.state.fl.us/Files/PDF/Publications/Reports/General/Factsandfigures/March%202017.pdf

Guikema SD, Quiring SM, Han SR (2010) Prestorm estimation of hurricane damage to electric power distribution systems. Risk Anal 12:1744–1752

Han SR, Guikema SD, Quiring SM, Lee KH, Rosowsky D, Davidson RA, Han SR (2009) Estimating the spatial distribution of power outages during hurricanes in the Gulf coast region. Reliab Eng Syst Saf 94(2):199–210

Hasan S, Foliente G (2015) Modeling infrastructure system interdependencies and socioeconomic impacts of failure in extreme events: emerging R&D challenges. Nat Hazards 78:2143–2168

He M, Lin K-P (2015) Testing in a random effects panel data model with spatially correlated error components and spatially lagged dependent variables. Econometrics 3:761–796

Huang C, Liou JJH, Chuang Y (2014) A method for exploring the interdependencies and importance of critical infrastructures. Knowl-Based Syst 55:66–74

IFRC (International Federation of Red Cross and Red Crescent Societies) (2016) What is vulnerability? Retrieved August 2016 from https://www.ifrc.org/en/what-we-do/disaster-management/about-disasters/what-is-a-disaster/what-is-vulnerability/

Kelejian HH, Prucha IR (2007) HAC estimation in a spatial framework. J Econom 140:131–154

Klas M-E (2017). Is South Florida more prepared than it was 12 years ago with Wilma? Miami Herald (September 6). Retrieved March 2018 from http://www.miamiherald.com/news/state/florida/article171543712.html

Klinger C, Landeg O, Murray V (2014) Power outages, extreme events and health: a systematic review of the literature from 2011 to 2012. PLOS Curr Disasters 2014 Jan 2. Edition 1. https://doi.org/10.1371/currents.dis.04eb1dc5e73dd1377e05a10e9edde673

Kraushar ML, Rosenberg RE (2015) A community-led medical response effort in the wake of Hurricane Sandy. Disaster Med Public Health Prep 9(4):354–358

Lai BS, Lewis R, Livings M, La Greca AM, Esnard A-M (2017) Posttraumatic stress symptom trajectories among children after disaster exposure: a review. J Trauma Stress 30:571–582

Larsen T, Porter K, Zadeh M, Van Anne C, Scawthorn C (1996) Impact of Hurricane Andrew on performance, interaction, and recovery of lifelines. EQE Int. Retrieved July 2018 from http://www.sparisk.com/pubs/Larson-1996-Andrew-Lifelines.pdf

Laska S, Morrow B (2006) Social vulnerabilities and Hurricane Katrina: an unnatural disaster in New Orleans. Mar Technol Soc J 40(4):16–26

Liévanos RS, Horne C (2017) Unequal resilience: the duration of electricity outages. Energy Policy 108:201–211

McRoberts DB, Quiring SM, Guikema SD (2016) Improving hurricane power outage prediction models through the inclusion of local environmental factors. Risk Anal. https://doi.org/10.1111/risa.12728

Miller K (2016) Record-shattering Hurricane Wilma hit Florida 11 years ago today. Palm Beach Post. 24 October 2016. Retrieved March 2018 from http://weatherplus.blog.palmbeachpost.com/2016/10/23/record-shattering-hurricane-wilma-hit-florida-11-years-ago-monday/

Miller TR, Chester M, Munoz-Erickson TA (2018) Rethinking infrastructure in an era of unprecedented weather events. Issues Sci Technol Nat Acad Sci Eng Med Winter 2018:46–58

Mitsova D, Sapat A, Esnard A-M, Lamadrid A (2018) An exploratory framework to examine the interdependent effects of critical infrastructure breakdowns on the emergency services sector (ESS) in extreme events. Working paper, Florida Atlantic University

Murià-Vila D, Jaimes MÁ, Pozos-Estrada A, López A, Reinoso E, Chávez MM, Fernando Peña F, Sánchez-Sesma J, López O (2018) Effects of hurricane Odile on the infrastructure of Baja California Sur, Mexico. Nat Hazards 91(3):963–981

Nateghi R, Guikema SD, Quiring SM (2011) Comparison and validation of statistical methods for predicting power outage durations in the event of hurricanes. Risk Anal 31:1897–1906. https://doi.org/10.1111/j.1539-6924.2011.01618.x

Peacock WG, Girard C (1997) Ethnicity and segregation. In: Peacock WG, Morrow BH, Gladwin H (eds) Hurricane Andrew: Ethnicity, gender, and the sociology of disaster. Routledge, New York, pp 191–205

Peacock WG, Van Zandt S, Henry D, Grover H, Highfield W (2012) Social vulnerability and Hurricane Ike: Using social vulnerability mapping to enhance coastal community resilience in Texas. In: Bedient PB (ed) After Ike: severe storm prediction, impact, and recovery on the Texas Gulf coast. Texas A&M University Press, Collge Station, pp 66–81

Peeters L, Chasco C (2006) Ecological inference and spatial heterogeneity: an entropy-based distributionally weighted regression approach. Pap Reg Sci 85(2):257–276

Tonn GL, Guikema SD, Ferreira CM, Quiring SM (2016) Hurricane Isaac: a longitudinal analysis of storm characteristics and power outage risk. Risk Anal 36:1936–1947. https://doi.org/10.1111/risa.12552

Zimmerman R (2016) Resilient urban infrastructure for adapting to environmental disruptions. In: Seto KC, Solecki WD, Griffith CA (eds) Handbook on urbanization and global environmental change. Routledge, London, pp 488–512

Zimmerman R, Farris C (2010) Infrastructure impacts and adaptation challenges. Ann N Y Acad Sci 1196:63–85

Zimmerman R, Zhu Q, de Leon F, Guo Z (2017) Conceptual modeling framework to integrate resilient and interdependent infrastructure in extreme weather. J Infrastruct Syst 23(4):04017034

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