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ORIGINAL PAPER

Assessment of the hurricane-induced power outages from a demographic, socioeconomic, and transportation perspective

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Abstract Natural disasters have devastating effects on the infrastructure and disrupt every aspect of daily life in the regions they hit. To alleviate problems caused by these disasters, first an impact assessment is needed. As such, this paper focuses on a two-step methodology to identify the impact of Hurricane Hermine on the City of Tallahassee, the capital of Florida. The regional and socioeconomic variations in the Hermine's impact were studied via spatially and statistically analyzing power outages. First step includes a spatial analysis to illustrate the magnitude of customers affected by power outages together with a clustering analysis. This step aims to determine whether the customers affected from outages are clustered or not. Second step involves a Bayesian spatial autoregressive model in order to identify the effects of several demographic-, socioeconomic-, and transportation-related variables on the magnitude of customers affected by power outages. Results showed that customers affected by outages are spatially clustered at particular regions rather than being dispersed. This indicates the need to pinpoint such vulnerable locations and develop strategies to reduce hurricane-induced disruptions. Furthermore, the increase in the magnitude of affected customers was found to be associated with several variables such as the power network and total generated trips as well as the demographic factors. The information gained from the findings of this study can assist emergency officials in identifying critical and/or less resilient regions, and determining those demographic and socioeconomic groups which were relatively more affected by the consequences of hurricanes than others.

Keywords Hurricane impact assessment · Power outages · Socioeconomic analysis · Community resilience · Bayesian spatial autoregressive analysis

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1 Introduction

Natural disasters such as hurricanes have devastating effects on the infrastructure and disrupt every aspect of daily life in the regions they hit. Communities living in these regions suffer from the adverse consequences of hurricanes; therefore, emergency officials are responsible to find solutions in order to alleviate the problems caused by these disasters. Although a sizable number of major hurricanes have struck the US Gulf States such as Florida previously, several areas of this hurricane-prone region have never seen landfalls in the last 30 years. For example, Hurricane Hermine was the first hurricane to make landfall in Florida on September 2, 2016, since Hurricane Wilma in 2005, and was the first hurricane to directly hit Apalachee Bay since Hurricane Alma in 1966 (Berg 2016). As a result of Hurricane Hermine, a large region in the Northwest Florida endured power outages, food shortages, and roadway disruptions (Morris and Johnson 2016). At a local level, Hermine left 100,000 residents without power in the City of Tallahassee, the capital of Florida, knocking out trees, power lines, and shutting down stores and businesses for days (Berg 2016; Morris and Johnson 2016; SERT 2017). In addition, this region was also affected adversely by the Hurricane Irma recently.

Previous studies have investigated the effects and consequences of hurricanes through spatial and statistical models. For example, a spatial and statistical analysis was conducted in Demiroluk and Ozbay (2015) to predict the treefalls during a hurricane using several predictors such as precipitation, roadway density, and wind speed via a hierarchical Bayesian model. Authors identified regions which possess higher risk of treefalls based on varying wind speeds. Moreover, it was shown that roadway density and wind speed were the most important variables affecting the treefall probability. The power system performance and power outages, on the other hand, have been of significant interest in the literature regarding the adverse consequences of hurricanes. For example, the power system performance and power outages were investigated by Davidson et al. (2003) during five hurricanes at South and North Carolina in the USA. Authors examined the number of outages, affected customers, and the geographic distribution of disruptions as well as the type of failed power system components. The magnitudes of disruptions were found to be highly correlated with the maximum wind speed. Environmental factors were also used to predict the number of hurricane-related power outages, which were stated to be essential to prepare the power system prior to a hurricane landfall (Quiring et al. 2011; Nateghi et al. 2014; Mcroberts et al. 2016). Mcroberts et al. (2016) proposed a two-phase estimation model using different environmental characteristics such as elevation, land cover, soil, precipitation, and vegetation characteristics in addition to speed and duration of winds. Results showed that inclusion of environmental characteristics and two-phase modeling substantially increased the prediction accuracy compared to previous models. The importance of environmental factors (e.g., soil characteristics and elevation) on the power outage was previously shown by Quiring et al. (2011).

To predict power outages and duration of these outages, researchers proposed various approaches such as negative binomial regression (Liu et al. 2005), generalized additive models (Han et al. 2009), spatial generalized mixed models (Liu et al. 2008), and random forest methods (Nateghi et al. 2014). For instance, a random forest model approach was adopted in Nateghi et al. (2014) using variables such as wind speed, wind duration, protection of power system, power system components, length of power lines, soil characteristics, precipitation, land slope, elevation, and land cover. They found that wind characteristics, precipitation, and soil characteristics (e.g., soil moisture level) were the most effective variables on the duration of power outages. In general, we observed that the power outage prediction studies usually relied on some common variables. These variables can be listed as hurricane characteristics (e.g., wind speed and duration, precipitation), geographical characteristics (e.g., land cover, elevation, soil type and features, vegetation, tree type), and power system characteristics (e.g., system components, electricity poles, power line lengths, protective systems).

The assessment of different aspects of hurricane impact has been as important as predicting power outages. For example, $410 million loss was estimated for State of Virginia through simulating various hurricane scenarios that will lead workforce losses due to absence (Akhtar and Santos 2013). In addition to economic loss, several studies paid attention to vulnerability and resilience of different demographic and socioeconomic groups as well as impacts of hurricanes and power outages on these groups (Lindell and Prater 2003; Gabe et al. 2005; Bjarnadottir et al. 2011; Bian and Wilmot 2017). For instance, Congressional Research Services' report on the impact of the Hurricane Katrina showed that the poor and African-American population suffered the most due to the storm (Gabe et al. 2005). Considering this important association between demographics/socioeconomics and hurricane impact, Bjarnadottir et al. (2011) developed a social vulnerability index for coastal communities using factors such as race, age, gender, and socioeconomic status, which also showed social vulnerability is driven by these factors. Another study focused on daily power outages rather than hurricane-induced ones (Liévanos and Horne 2017). This study examined the community resilience to daily power outages considering a few socioeconomic- and transportation-related variables such as the disadvantage of Native Americans, distance to the nearest hospital, and distance to the major roadway. Authors have also used a spatial regression approach using these variables in order to interpret the outlying reasons behind the daily power outage durations.

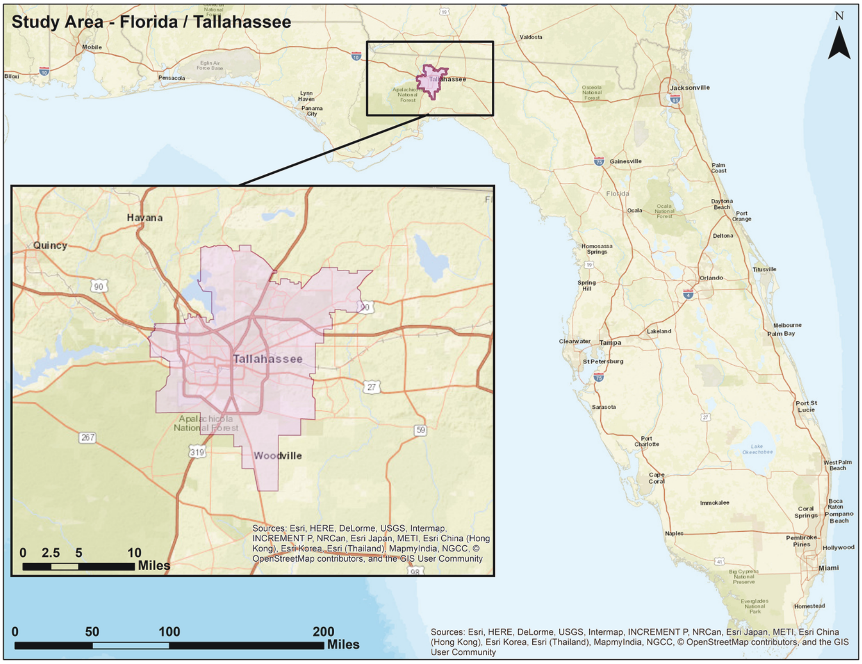
In this study, we investigated the impact of Hurricane Hermine both on the City of Tallahassee infrastructure and on the communities of the city. The prominent consequence of the hurricane—power outages, was examined spatially and statistically in order to comprehend the regional variations of Hermine's impact on the different demographic and socioeconomic groups. This analysis also led to the identification of the factors such as the type of power lines or wind speed which drive the magnitude of this impact. In order to perform this, a two-step approach was adopted. First step includes (a) a spatial analysis to illustrate the magnitude of customers affected by power outages in different regions, and (b) a spatial autocorrelation analysis based on Moran's I index (Ord and Getis 1995; Koenig 1999) together with a clustering analysis based on Anselin Local Moran's I index (Anselin 1995; McCullagh 2006). The spatial analysis was conducted in order to determine the spatial distribution of the customers affected from outages. Second step involves a statistical analysis to model the number of customers affected by power outages over the total population (i.e., percentage of affected customers) using several variables related to demography, socioeconomics, power system components (e.g., underground/overhead power lines), roadway disruptions, and transportation. Note that, in this study, the objective is to assess the impact of Hurricane Hermine on the Tallahassee communities rather than attempting to predict the locale of power outages. That is, we use demographic-, socioeconomic-, and transportation-related variables in order to answer the following question: Where and why post-hurricane treatments and remedies of the city agencies should focus?

2 Case study area and data description

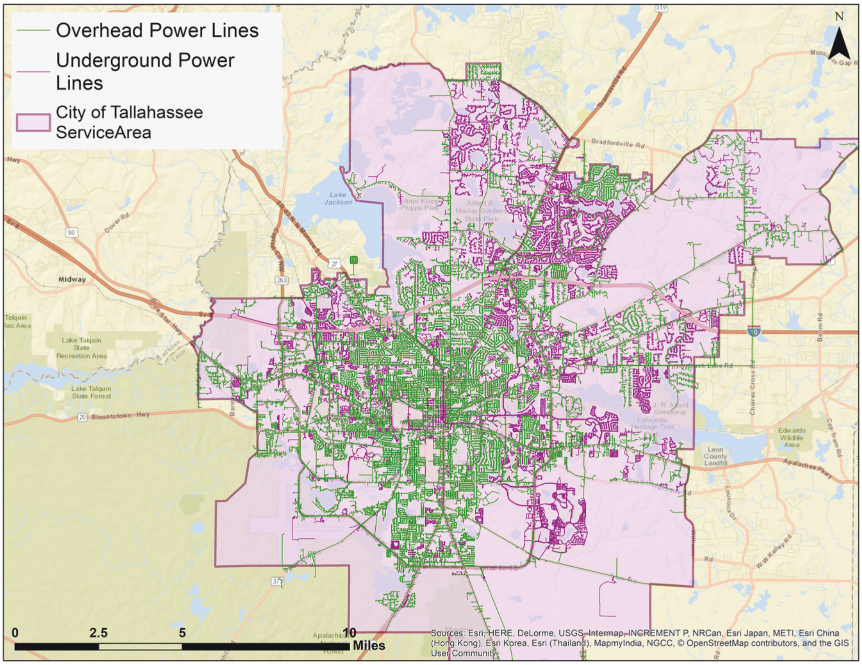
This section presents a case study application in the City of Tallahassee, the capital of Florida, which was hit by Hurricane Hermine on September 2, 2016 (Fig. 1a). Tallahassee is also a home to two universities and has a population of 190,894, which makes it a midsize city and a considerable urban region. In this paper, several datasets were used to conduct the proposed case study application. These datasets include those that are related to the city infrastructure (power lines, failed power system components and roadway closures due to fallen trees, provided by the City of Tallahassee—Figs. 1b, c and 2, respectively), 2010 Census data (U.S. Census Bureau 2010) (census block groups—Fig. 2), and maximum measured wind speeds at weather stations in Tallahassee (WeatherSTEM 2017) (Fig. 2).

The City of Tallahassee is a full-service municipality providing essential services to the region: electric, gas, water solid waste, sewer, public works, airport, mass transit, etc. It was one of the first public utilities in the USA to implement a full-scale Automated Metering Infrastructure in 2009. Power outage data were gathered through the "ping" operation for the power network, which identifies the outages. "Ping" data contain unresponsive devices (e.g., circuit breakers, reclosers, fuses, switches, transformers, and service points) and the following information: the feeder they belong to, dispatch remarks, time of outage, time of restoration, duration for the outages, and number of customers affected. These data are sampled hourly data which shows the number and location of customers at distribution level who experience outage after the hurricane. Note that the cascading failure is not considered in this study since cascading effects happened in the range of seconds and minutes not hours. So, they do not reflect in hourly data. Therefore, cascading effect in a dynamic form is not part of this work; however, the impact of cascading is shown as the customer outages, and that outage is caused by the direct effect of hurricane and cascading effect. The restoration covers a time frame from September 1 to September 10, 2016, affecting 60,928 customers (Berg 2016). The failed power system components were used to calculate number of customers affected by power outage at each US census population block group. Note that the failure of these components results in different outcomes in the context of affected customers. For instance, service point failures usually indicate one or a few number of customers suffering from the outage. Failure of circuit breakers, on the other hand, affects a large number of customers since these components serve multiple power lines connected to many customers.

Roadway closures were identified through online requests and requests through a mobile app called DigiTally (DigiTally 2017), which are both maintained by the City of Tallahassee. DigiTally establishes a platform to connect residences directly with City of Tallahassee, which helps communicating more effectively and efficiently to resolve issues in the community. Through these systems, residents can file requests for any issues and monitor others. During Hurricane Hermine, 776 roadway closures/disruptions due to tree failures were reported in a 1-week window. Note that, although this may not be the whole roadway closures that happened as a result of fallen trees, the City of Tallahassee officials have ensured the research team that this dataset included all the major roadway closures the city has experienced. The total number of roadway closures together with the average duration of closure was determined for each US census population block group and then used in the Bayesian spatial autoregressive model.

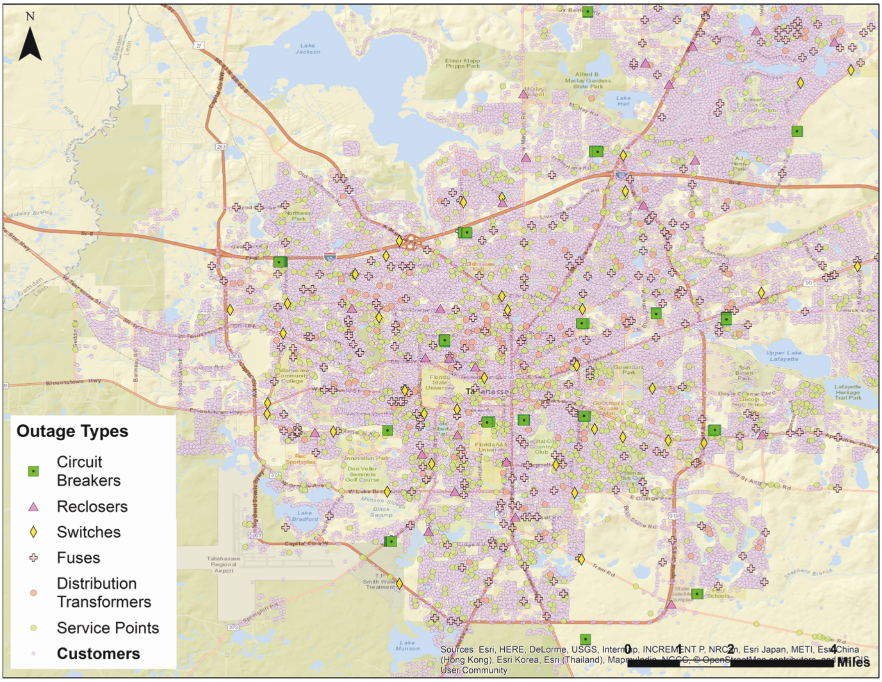


(a)



(b)

Fig. 1 Overview of the study area and data: **a** study area, **b** power infrastructure, **c** customers and failed components of the power infrastructure



(c)

Fig. 1 continued

3 Methodology

This study consists of two different methodological approaches to investigate the impact of Hurricane Hermine both on the infrastructure and on the communities of the City of Tallahassee: spatial and statistical analyses. Spatial analyses include: (a) mapping the affected customers, (b) determining the density distribution of the magnitude of power outages using a kernel density estimation (KDE)-based approach, (c) identifying the spatial autocorrelation (using Global Moran's I index) between power outage magnitudes of affected customers to discover whether there is a clustering pattern or not, and (d) illustrating those power outage clusters using the Local Moran's I index, if there is a clustering pattern identified by the Global Moran's I index. Following the spatial analysis, a statistical modeling approach was utilized to comprehend the intricacy of the power outages. As such, a Bayesian spatial autoregressive model was adopted to conduct a statistical analysis due to its advantage in modeling spatially distributed datasets which possess inherent spatial correlation between observations. This type of Bayesian modeling approach was preferred due to its power when sample size is relatively small (Dunson 2001; De Winter et al. 2009). A flowchart illustrating overall methodology is provided in Fig. 3.

3.1 Spatial analysis

The power outage data revealed the spatial distribution of affected customers. This information was used to obtain the power outage density map shown in Fig. 4. Figure 4a

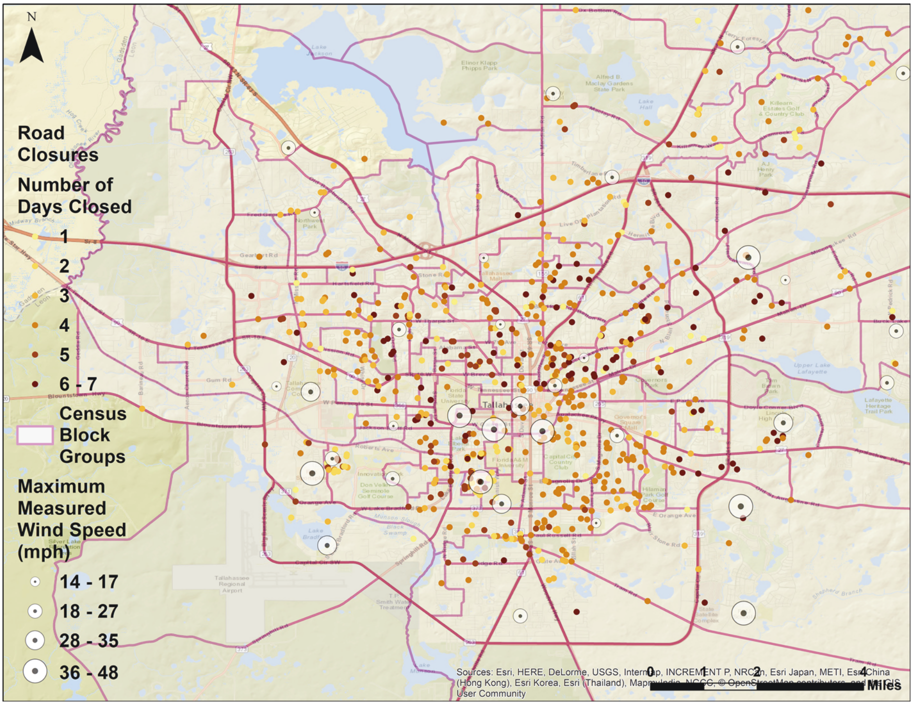


Fig. 2 US Census population block groups, hurricane-related roadway closures due to fallen trees and maximum wind speed measurements at weather stations

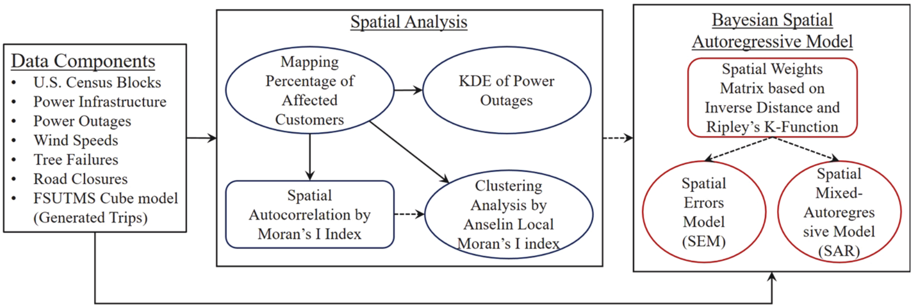
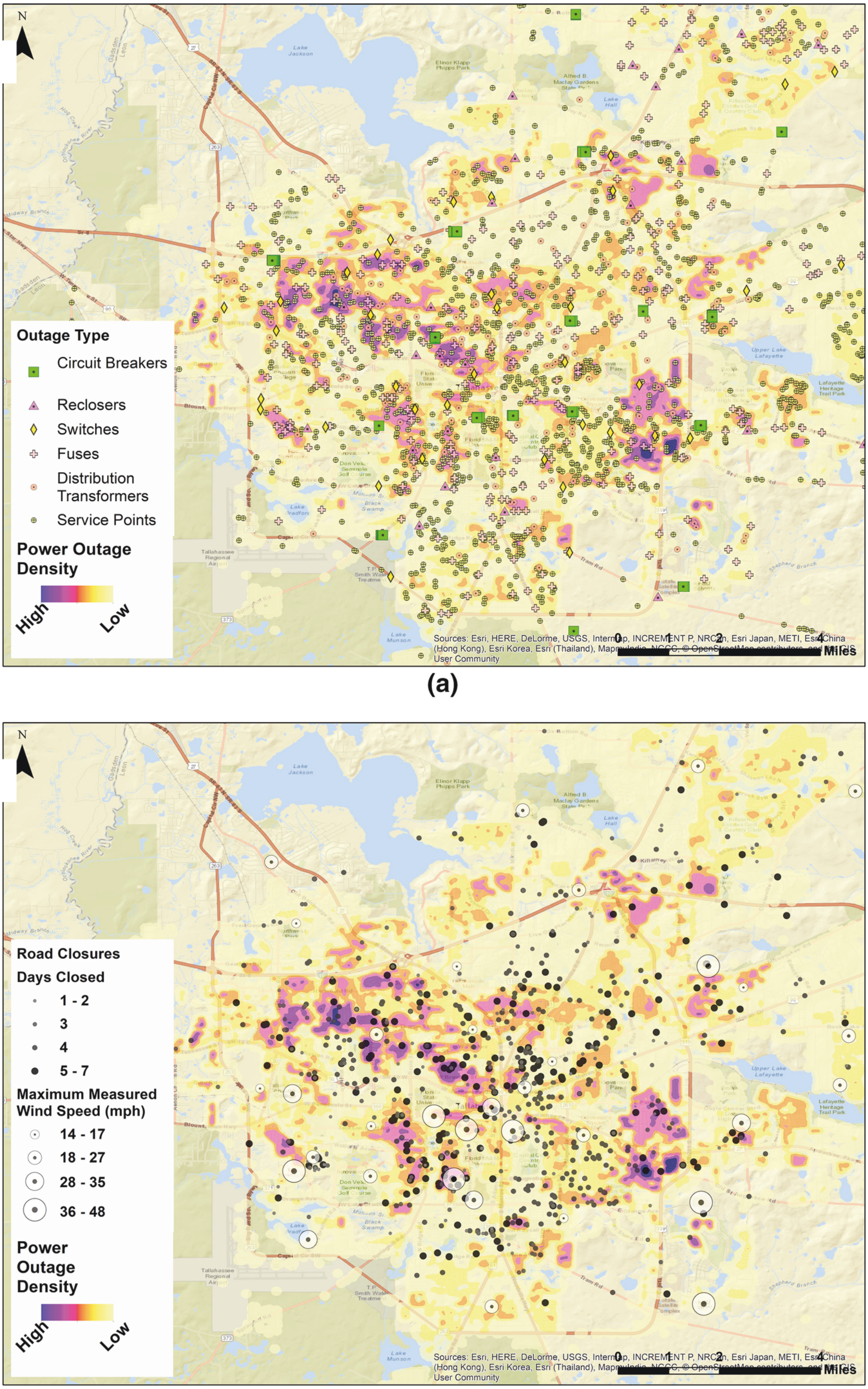


Fig. 3 Methodology flowchart

shows the failed power system components along with the power outage densities throughout the study region. Figure 4b, on the other hand, displays how roadway closures and the power outage densities are related. It is clear from the figures that a direct relationship between roadway closure intensity and the elevated power outage density exists since roadway closures, particularly those with longer durations, were more frequent at those regions with high outage densities. The power outage density was calculated based on the spatial distribution of affected customers using a kernel density estimation (KDE) approach (Brunsdon 1995) in ArcGIS software (ESRI 2014). This was followed by determining the total number of affected customers in each census block group to be able



(a)

(b)

Fig. 4 Power outage density along with **a** failed power system components and **b** roadway closures to observe the regional variation of the power outages in the city. As such, two different metrics were calculated: (1) total number of affected customers and (2) total number of affected customers divided by the total population of each census block group (i.e., percentage of affected customers). Identifying the affected customers in each census block group provided a visual basis to compare different regions in terms of the impact of the hurricane. A spatial autocorrelation analysis was conducted based on Moran's I index (Ord and Getis 1995; Koenig 1999) to determine whether there is a spatial clustering pattern for customers affected from outages. This was followed by a clustering analysis which was conducted based on Anselin Local Moran's I index (Anselin 1995; McCullagh 2006) in order to identify those census block group clusters based on the magnitude of affected customers. Both analyses were conducted using the ArcGIS software (ESRI 2014). This spatial analysis aimed to highlight those regions which compel special attention for post-hurricane treatments (e.g., improving infrastructure, building redundant systems, and providing generators). In addition, findings pinpoint the critical locations city can focus on in order to alleviate future outage problems. The regional variations of power outages in the City of Tallahassee are provided in Results section.

3.2 Bayesian spatial autoregressive model

Bayesian spatial autoregressive modeling was used to assess the impact of hurricane on the different demographic and socioeconomic groups as well as to identify factors such as type of power lines or wind speed which drive the magnitude of this impact. The necessity of implementing spatial autoregressive model arose from the spatial autocorrelation analysis (Moran's I) conducted for the residuals obtained from ordinary least-squares analysis (Ord and Getis 1995; Koenig 1999). Findings of this analysis are provided in Results section. The demographic and socioeconomic variables were provided in the US Census data (U.S. Census Bureau 2010), whereas power outages and roadway closures were provided by the City of Tallahassee. Moreover, maximum wind speeds at weather stations were collected from the WeatherSTEM (WeatherSTEM 2017), and the total generated trips at census block groups were obtained from the Capital Region Cube model (Citilabs 2016; FSUTMS 2017). The list of candidate variables for the model together with their descriptive statistics and definitions is provided in Table 1. The correlations between these candidates were tested using Pearson correlation coefficient measure (Fig. 5), and highly correlated variables such as percentage of white and African-American population were identified. Then, the potential models were investigated, and the final model along with its variables was determined. Note that the dependent variable of the analysis is total number of affected customers over the total population (i.e., percentage of affected customers). This metric is similar to the "System Average Interruption Frequency Index" (SAIFI) proposed by IEEE (IEEE 2012); however, the denominator in this paper is the total population rather than total customers given in SAIFI.

The spatial autoregressive modeling is a particular approach applicable to spatially distributed datasets which possess an inherent spatial correlation between observations. This type of data is known to produce systematically varying residuals when implemented with models that disregard spatial relations between observations (i.e., generalized linear models) (LeSage 1997). The reason behind the Bayesian approach was as follows: (a) the sample size of the study data was relatively small ($N = 160$), and (b) the constant variation of errors and normality assumption inherent to maximum likelihood (ML) estimation was relaxed. The Bayesian and ML approaches are known to result in similar estimates when sample size is large enough ($N > 200$) (Dunson 2001; De Winter et al. 2009). However,

Table 1 Descriptive statistics and definitions of candidate variables

Variables	Min	Max	Mean	Med	SD	Definition
White (%)	0.003	0.972	0.607	0.656	0.263	Percentage of white population
African-American (%)	0.011	0.981	0.328	0.266	0.266	Percentage of African-American population
Young (18−) (%)	0	0.427	0.186	0.197	0.086	Percentage of 18 years and younger population
Aging (65+) (%)	0	0.591	0.102	0.092	0.078	Percentage of 65 years and older population
Average family size	0	4	2.856	3	0.548	Average family size in a census block group
Above poverty (%)	0	1.487	0.723	0.761	0.297	Percentage of people living above poverty level
Below poverty (%)	0	1.117	0.225	0.139	0.24	Percentage of people living below poverty level
College Degree (%)	0	0.417	0.16	0.156	0.081	Percentage of people with at least college degree
Use of car for transportation (%)	0	0.857	0.447	0.452	0.164	Percentage of people relying on private cars for transportation
Use of public transportation (%)	0	0.142	0.008	0	0.021	Percentage of people using public transportation for travel purposes
Median family income	0	16	5.837	5.045	3.599	Median income of families living in a census block group (divided by 10,000)
Zero vehicle ownership (%)	0	0.404	0.032	0.015	0.051	Percentage of people with no vehicle ownership
Number of road closures	0	28	4.869	3	5.199	Total number of road closures within the census block group
Average day roads closed	0	5	1.854	1.991	1.173	Average duration of road closures (days)
Total length of underground (UG) power lines	0	63	6.049	3.049	8.728	Total length of underground power lines (divided by 10,000)
Total length of overhead (OH) power lines	0.061	30	8.641	7.752	5.4	Total length of overhead power lines (divided by 10,000)
Total length of power lines	2.053	698	146.899	118.2	106.2	Total length of power lines
Maximum wind speed	14	47	24.519	22	9.447	Maximum wind speed measured during hurricane
Total generated trips/total population	0	44	3.642	1.985	5.152	Total daily travels generated in a census block group over total population

Min minimum, *Max* maximum, *Med* Median, *SD* standard deviation

one of the advantages of Bayesian models is observed when there is this aforementioned small sample size problem, which prevents making consistent and accurate estimates using the ML approach (Dunson 2001). In this study, there are 160 census block groups used to model the power outages, which compels the use of Bayesian approaches rather than ML-based ones (De Winter et al. 2009). Furthermore, the Bayesian extension of spatial autoregressive model introduces the concept of spatial heterogeneity which relaxes the

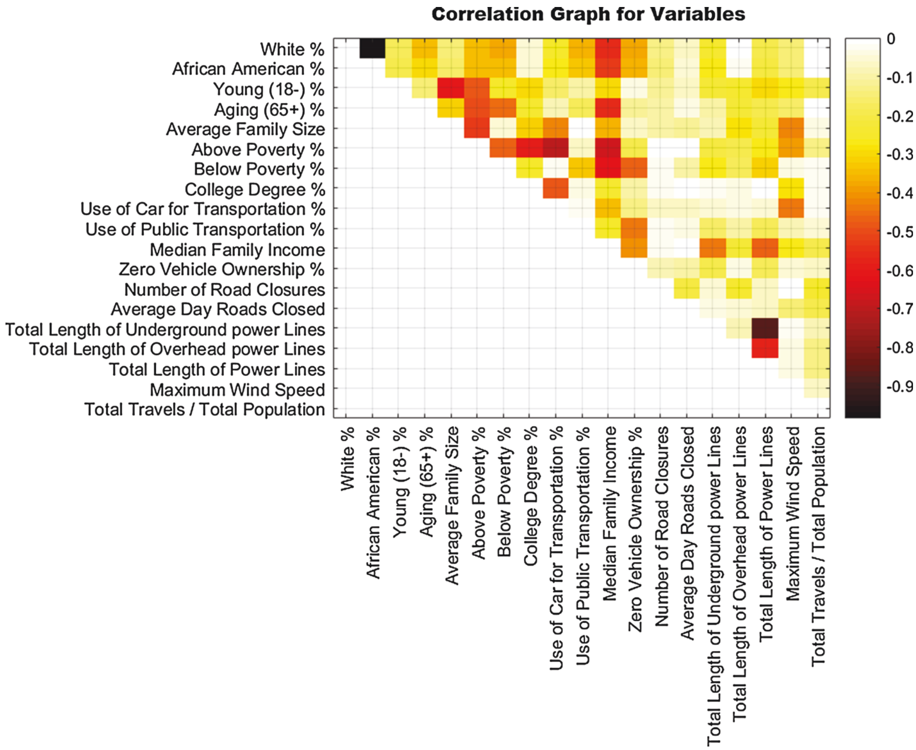


Fig. 5 Correlation chart of candidate variables

assumptions of normality and constant variation of errors. A detailed description and discussion on the Bayesian inference can be found in Gelman et al. (2003). The structure of Bayesian spatial autoregressive model is given below (LeSage 1997):

$$
\begin{aligned}
y &= \rho \boldsymbol{W}_1 y + \boldsymbol{X}\beta + u \\
u &= \lambda \boldsymbol{W}_2 u + \epsilon \\
\epsilon &\sim N\left(0, \sigma^2 V\right) \\
V &= \mathrm{diag}(v_1, v_2, \ldots, v_n)
\end{aligned}
\tag{1}
$$

where y is an n by 1 vector of observations, $\boldsymbol{X}$ is n by k matrix of model variables, β is k by 1 vector of variable coefficients, $\boldsymbol{W}_1$ and $\boldsymbol{W}_2$ are n by n row-standardized (rows sum to 1) spatial weight matrices also known as contiguity matrices involving the distance relations between observations and having zeros in diagonal. ρ and λ are the spatial autoregressive parameters, ϵ is a normally distributed error term with zero mean and non-constant variance with different values for each observation through V. The magnitudes of v_i which introduce spatial heteroscedasticity via non-constant variance were estimated by the Bayesian approach.

The Bayesian modeling approach compels the identification of prior distributions for parameters based on the prior knowledge about the variables and their parameters. However, this prior knowledge is generally not available, and prior distributions are chosen for convenience rather than any prior information about the actual parameter distributions.

Fig. 6 Spatial distribution of power outages in each census block group together with wind speed measurements: **a** total number of affected customers and **b** total number of affected customers over total population

The posterior distributions of parameters are determined based on these prior distributions (Gelman et al. 2003).The Bayesian specification of the model as used in this study is given below (LeSage 1999):

$$\begin{aligned} \beta &\sim N(c, T) \\ \sigma &\sim (1/\sigma) \\ r/v_i &\sim \mathrm{ID}\chi^2(r)/r \\ r &\sim \Gamma(m, k) \end{aligned} \tag{2}$$

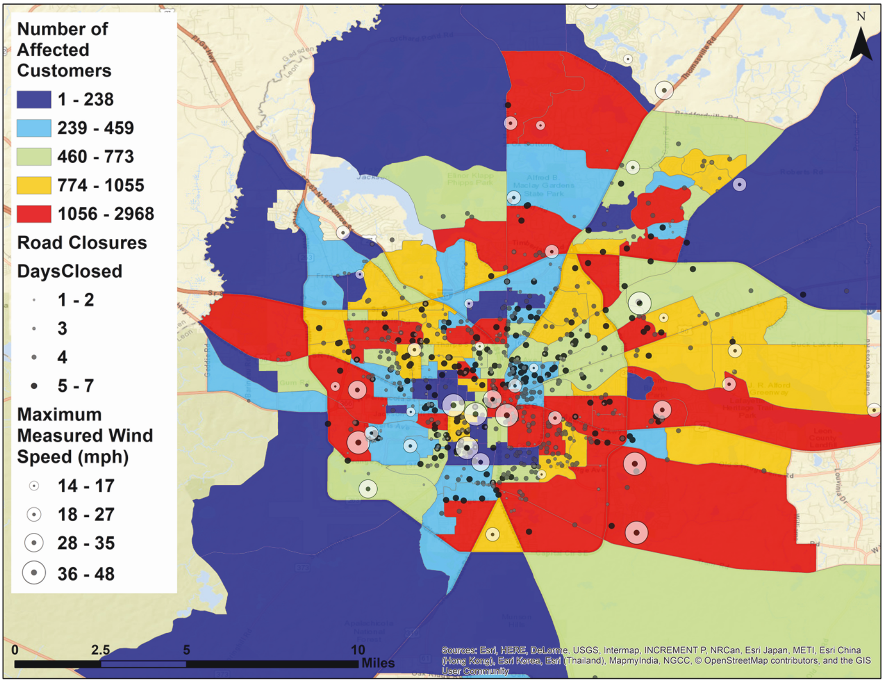
where a normal prior was introduced to β and a diffuse prior was introduced into σ. Variance terms, v_i, are fixed, and they were estimated based on the informative prior distribution of $\chi^2(r)/r$ with a gamma distributed parameter r.

There are two special models that can be derived based on the general model specification given in Eq. 1 through the imposed restrictions on spatial weight matrices. First model involves setting W_1 to zero which creates spatially correlated disturbances with a classical regression model, or the so-called spatial errors model (SEM). Setting W_2 to zero, on the other hand, produces a mixed regressive—spatial autoregressive model (SAR) which is also known as the spatial lag model (LeSage 1997; Anselin 2002). We tested the general proposed model as well as these two special models in order to identify the best-fitting model to the used data.

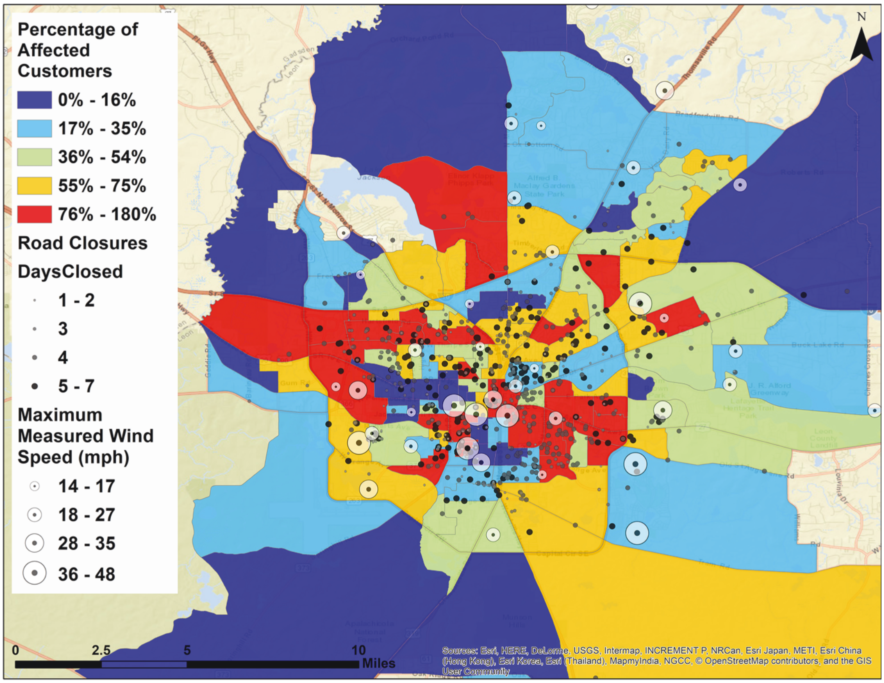
4 Results

4.1 Spatial analysis results

The first step of the analysis involves the spatial investigation of power outages induced by the Hurricane Hermine. The analysis was conducted to identify those critical locations which were affected the most. In order to achieve this, the total number of customers affected by outages in each census block group was determined, and two metrics—total number of affected customers and percentage of affected customers—were calculated (Fig. 6). Figure 6a, b displays a slight variation due to the normalization by the total population living in the census block groups. Figure 6a shows that power outages were more or less spread over the City of Tallahassee. It is observed that there were customers highly affected by the outages in the whole city. Figure 6b, on the other hand, shows that the power outages were mostly clustered in the Northwest and Mid-Southeast of the City of Tallahassee when the focus is on the percentage of affected customers. Note that red regions have relatively decreased in the Southeast compared to Fig. 6a. This means that even though there are a substantial number of affected customers in the Southeast Tallahassee, the number of affected customers is not that high compared to the total population. Furthermore, roadway closures were displayed along with the affected customers in both maps. It is apparent from the maps that there is a higher concentration of roadway closures in those regions with elevated percentage of affected customers. This indicates a close relationship between roadway closures and power outages, which is expected since fallen


Number of Affected Customers
1 - 238
239 - 459
460 - 773
774 - 1055
1056 - 2968
Road Closures
DaysClosed
1 - 2
3
4
5 - 7
Maximum Measured Wind Speed (mph)
14 - 17
18 - 27
28 - 35
36 - 48
N
0
2.5
5
10
Miles
Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community

(a)


Percentage of Affected Customers
0% - 16%
17% - 35%
36% - 54%
55% - 75%
76% - 180%
Road Closures
DaysClosed
1 - 2
3
4
5 - 7
Maximum Measured Wind Speed (mph)
14 - 17
18 - 27
28 - 35
36 - 48
N
0
2.5
5
10
Miles
Sources: Esri, HERE, DeLorme, USGS, Intermap, INCREMENT P, NRCan, Esri Japan, METI, Esri China (Hong Kong), Esri Korea, Esri (Thailand), MapmyIndia, NGCC, © OpenStreetMap contributors, and the GIS User Community

(b)

trees are the most prominent cause of these two disruptions. Nevertheless, roadway closure can also stem from damages inflicted to the power system components. For instance, similar to fallen trees, fallen electricity poles or other failed power feeder lines can also lead to roadway closures. Furthermore, power outages can also affect traffic signalization of the city which would further cripple the transportation network and cause closure of roadways due to safety concerns.

Figure 7a, b, on the other hand, demonstrates the spatial clustering of census block groups based on the magnitude of affected customers. Although the visual inspection of Fig. 6a, b does not show a clustering pattern, spatial autocorrelation (Global Moran's I) and clustering analysis (Local Moran's I) results disclosed that there is a clustering pattern based on both number of affected customers and percentage of affected customers. For instance, Fig. 7a reveals that there is a high clustering of number of affected customers in the Mid-Southeast Tallahassee and a smaller region in the Northwest Tallahassee. This clustering pattern shifted westward when percentage of affected customers is considered, as shown in Fig. 7b. This type of visualization of the outage data can be helpful for the city officials to pinpoint those critical locations for post-hurricane treatments. However, there is a need for more concrete statistics-based analyses in order to verify these results, which will be presented in the next section.

4.2 Spatial autoregressive model results

To assess the necessity for a spatial autoregressive model, Moran's I statistics was calculated first for the residuals of an ordinary least-squares analysis. The result for this analysis (*Moran's I: 0.18, Moran' I statistics: 4.76 > 1.96, hypothesis of no spatial correlation rejected*) clearly showed that there is an inherent spatial relationship between observations that cannot be captured by non-spatial models. This finding indicates that a linear (or nonlinear) model which disregard a spatial correlation between observations is not appropriate for the data used in this study. Given the need for spatial models, we created the spatial weights matrix required for spatial model. As such, we first identified the distance that provides the highest spatial correlation between observations through a Ripley's K function approach (Gatrell et al. 1996), which resulted in 6.25 miles. Then, a spatial weights matrix was created by using this distance (6.25 mi) as threshold value. The spatial relationship between observations was conceptualized by the inverse distance method.

In this paper, three spatial autoregressive models were tested, namely general, SAR, and SEM models, in order to find the best-fitting approach through checking the statistical significance of spatial autoregressive model parameters ρ and λ (LeSage 1999). Table 2 shows that parameters of both SAR and SEM models are statistically significant at a 5% significance level, while parameters of the general model are not significant. This finding indicates that SAR or SEM model is more appropriate than the general model. A further examination was conducted to check the spatial correlation between residuals of the SAR model. Spatial autocorrelation analysis indicated that there still exists a spatial dependence in the residuals of SAR model, implying that spatial correlation between observations is not fully captured. Therefore, SEM model appears to fit the study data better than SAR model. Nevertheless, we presented results for both models in order to show a better picture of the spatial model findings.

Result of the spatial autoregressive modeling shows that most of the variables (9 out of 12) have statistically significant effects on the percentage of affected customers at a significance level of 10% (Table 3). Moreover, both approaches (SEM and SAR) appear to

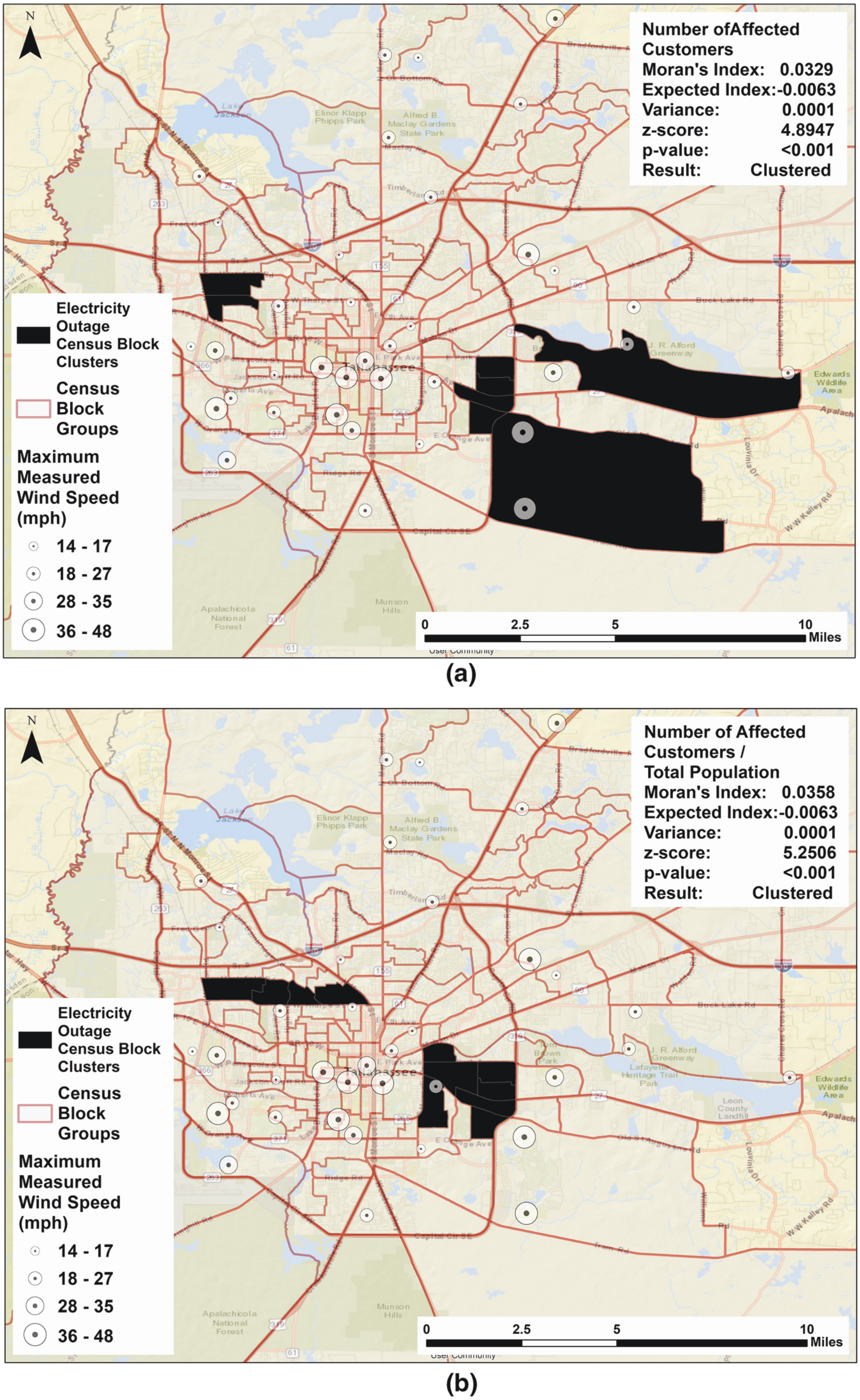


Fig. 7 Spatial autocorrelation and Local Moran's I results: **a** total number of affected customers and **b** percentage of affected customers

Table 2 Spatial model parameter significance

Parameters	General (p level)	SAR (p level)	SEM (p level)
ρ	0.393 (0.144)	0.523 (0.011)	–
λ	0.207 (0.601)	–	0.703 (0.004)

Table 3 Bayesian spatial autoregressive model results

Variables	SEM			SAR		
	β	p	$p < 0.1$	β	p	$p < 0.1$
Intercept	− 0.286	0.06	✔	− 0.506	0.00	✔
Young (18−) (%)	− 0.196	0.29	✗	− 0.345	0.15	✗
Aging (65 +) (%)	0.845	0.01	✔	0.815	0.01	✔
Average family size	0.077	0.08	✔	0.074	0.08	✔
College degree (%)	0.518	0.05	✔	0.575	0.04	✔
Car use for transportation (%)	0.320	0.03	✔	0.376	0.01	✔
Median family income	− 0.012	0.10	✔	− 0.014	0.05	✔
Number of road closures	0.007	0.07	✔	0.007	0.06	✔
Average day roads closed	0.063	0.00	✔	0.060	0.00	✔
$\sum$ length of OH power lines	0.010	0.02	✔	0.011	0.01	✔
$\sum$ length of UG power lines	0.001	0.40	✗	0.001	0.46	✗
Maximum wind speed	0.002	0.22	✗	0.002	0.20	✗
$\sum$ generated trips/$\sum$ population	0.007	0.06	✔	0.007	0.05	✔
λ	0.703	0.00	✔	–	–	
ρ	–	–		0.523	0.01	✔

Number of observations: 160, number of variables: 12

β Estimated coefficient mean, p p value, $\sum$ total, *SEM* spatial error model, *SAR* spatial mixed autoregressive model

produce similar results. "Aging (65 +) %" variable reveals that the higher the percentage aging population living in a census block, the higher the percentage of affected customers. This finding implies that the regions commonly populated by aging residents were highly affected by the power outages. Another interesting finding is that percentage of affected customers increases by the increasing "Average Family Size." This means that census block groups where larger families are living suffered power outages more significantly than other locations. This assessment also holds for "College Degree %" and "Car Use for Transportation %."

"Median Family Income," on the other hand, discloses a different pattern due to its' negative coefficient. That is, higher median family income seems to be associated with decreasing percentage of affected customers. One explanation for this finding might be the fact that higher-income families usually prefer in newly developed/developing parts of the city, where the infrastructure is relatively new and/or power lines are under the ground. For example, the coefficient of "Total Length of Overhead Power Lines" shows that the longer the overhead power lines, the higher the percentage of affected customers. The effect of

"Total Length of Underground Power Lines," on the other hand, is very small and not statistically significant even though it has a positive coefficient. Figure 1b shows that underground lines are more frequent at newly developed/developing areas than other parts of the city due to the ease of deployment of underground lines at newly developing areas. Consequently, regions that have overhead lines rather than underground lines appear to be more vulnerable to hurricanes, which is logical and expected.

Total number of roadway closures within each census block group and average duration of these closures directly reflect the impact of the hurricane, and in turn, there is a substantial association between power outages and these variables. A substantial amount of power outages could actually be a result of fallen trees on the power lines. As such, the higher the number of roadway closures and duration of these closures, the higher the number of percentage of affected customers. Similarly, "Maximum Wind Speed" variable is used as a measure to quantify the magnitude of the Hurricane Hermine. Surprisingly, the effect of wind speed is not as firm as the effect of roadway closures since it is not statistically significant. This means that, at the very least, there is a high variation in the effect of maximum measured wind speed on the power outages. This indicates that the maximum wind speed of the hurricane is relatively less effective by itself, and probably environmental factors such as presence of trees and poor infrastructure elevate the severity and disruptiveness of the hurricane. In other words, failed power components might be already in bad condition which would not be able to withstand even low-to-moderate wind speeds while components in good condition or with redundancy endured higher wind speeds without failing. Indeed, the power outages were mostly observed at periphery of the city where power system redundancy was questionable. Around the city center, on the other hand, power system redundancies seemed to prevent total outage despite higher wind speeds. Consequently, although wind speed may directly affect the failure of individual system components such as switches and feeders, failure of a system is more likely to be triggered by the combination of several factors (e.g., state of repair, redundancy, and wind speed). From a transportation point of view, results show that the regions that generate more trips were more affected by the power outages as "Total Generated Trips/Total Population" variable has a positive coefficient. This is critical since the total generated trips generally reflect the magnitude of travels starting from a zone and usually residential areas generate higher number of trips. Therefore, disruptions in these areas prolong the recovery period after the hurricane and in turn further cripple the economic and social life in the city. Nonetheless, it is important to note that the city center is observed to be relatively less affected by outages. This indicates that city may still be functioning since major government or business offices might not be as severely affected as the residential areas, which would enhance the economic recovery efforts. Therefore, it is critical to pay particular attention to the power system components in and around facilities such as governmental offices and big businesses. However, overall resilience of the city depends on the well-being of the citizens since people are the engines of the disaster response and recovery efforts which bring about importance of power system resilience in the residential areas.

5 Conclusions

In this study, the hurricane-induced power outages were investigated spatially and statistically in order to comprehend the regional variations of the hurricane's impact on the city infrastructure as well as different demographic and socioeconomic groups. This is performed through analyzing the data based on the adverse consequences of a recent

Hurricane Hermine that hit the City of Tallahassee. Spatial analysis was performed in order to identify the highly affected areas based on the "percentage of affected customers" metric. Spatial autoregressive modeling, on the other hand, provided critical information about the association between the magnitude of affected customers and several variables related to demographics, socioeconomics, infrastructure, transportation, and hurricane characteristics.

The information gained by such investigation of hurricane-induced power outages can assist emergency officials in identifying critical and less resilient regions, and determining those demographic and socioeconomic groups which were more affected by the adverse consequences of the hurricane. For example, the analysis showed that the higher the percentage of aging (65+) residents, the higher the percentage of affected customers. This indicates the need for addressing those problems related to infrastructure and power system components at those regions where more 65 + populations live. Another critical finding is that the magnitude of power outages appeared to be increasing in regions which generate more trips. This is critical since the total generated trips generally reflect the magnitude of travels starting from a zone, and usually residential areas generate higher number of trips. In addition, the roadway infrastructure also appears to be crippled in those regions. For a more resilient community, this transportation perspective should be considered, and disruptions in these areas should be prevented in order to maintain the economic and social quality of life in the city.

There are several limitations of this study. For example, there were not enough number of weather stations to find the maximum measured wind speeds to cover the whole study area, and there were a number of census block groups without wind speed measurements. Therefore, measurements of the wind stations closest to these census block groups were used in the analysis. This assumption might have created some errors related to estimating the effect of maximum wind speed on the magnitude of power outages. Furthermore, hurricane-related roadway closures were obtained from the online requests and the Digi-Tally database, which mainly shows online requests from the city residents. Therefore, it is possible that there may be other locations which were not reported online by the residents. This might be a drawback of data source in terms of reflecting the actual extend of roadway closures. Moreover, the impact of only Hurricane Hermine was investigated in this study due to data availability. However, as a future study, the impact of Hurricane Irma will be investigated and compared with the findings of this study if and when the data for this recent hurricane are available to the authors.

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