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Factors in the resilience of electrical power distribution infrastructures

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A B S T R A C T

One measure of the resilience of any dynamical system is the speed of return to equilibrium following perturbation. In electrical power distribution systems this may be approximated by the duration of unscheduled outages due to failure of the distribution system (i.e., excluding outages due to failure of the generation or transmission systems). We hypothesize that the resilience of power distribution systems depends on two main factors. One is the power distribution infrastructure, the biophysical environment within which it operates, and interactions between the two. The other is the priority given to restoration by the power company, and the effectiveness of the power company's response. To test this we modeled outage duration in the residential electrical power distribution system in part of the City of Phoenix, Arizona between 2002 and 2005. We found that while the type of infrastructure did not have a significant effect on outage duration, the interaction between infrastructure (overhead lines) and the biophysical environment (vegetation) did. We also found strong evidence that proximity to particular high priority emergency assets (i.e., hospitals) confers resilience on residential distribution systems. More generally, residential outage duration was found to be most spatially dependent up to around 1000 feet from an outage location. Overall, a spatial outage duration model provided a better fit to the data than a non-spatial model.

Introduction

Resilience is increasingly recognized to be an important dimension of the sustainability of a wide class of human, natural, and engineered systems (Adger, Hughes, Folke, Carpenter, & Rockstrom, 2005; Brock, Mäler, & Perrings, 2002; Turner et al., 2003; Walker et al., 2006). Resilience is commonly measured in one of two ways: by the size of the shock needed to dislodge a system from its current operational state (Holling, 1973), and by the speed with which a system returns to equilibrium after a disturbance (Pimm, 1984). In this paper we explore the resilience of an electric power distribution system in the second sense. Our measure of resilience is the speed with which the system returns to normal effectiveness after an accidental outage, approximated by the duration of the outage. We conjecture that resilience depends partly on the physical characteristics of the power distribution network, and partly on the effectiveness of network management. The physical characteristics of the network include whether it is 'loop' or 'radial' in design, whether power lines are above or below ground, how they interact with the biophysical environment and so on. The effectiveness of network management includes both the triage system that prioritizes responses to outages, and the efficiency of those responses.

The motivation for focusing on a 'speed of return' notion of resilience is that it is more directly related to the cost of system failure. The cost of power outages depends on their duration. In addition, we note that there exist data on outages, but not on the intensity of the shocks that cause them. Many studies indicate that the damage of an outage to a residential energy consumer increases linearly with the length of the interruption (Ahsan, 2004; Allan & Billinton, 1993; Brown, 2002; Kariuki & Allan, 1996). Billinton and Wangdee (2003) also show that the time of day, day of the week, and time of year matter. While the effect of interactions between environmental, infrastructural, and social conditions on duration of outages remains underexplored (Kwasinski, 2010), the impact of any one set of conditions is reasonably well understood. Chow, Taylor, and Chow (1996) show that outage duration is strongly correlated with the shocks that cause outages. Research on factors affecting outage duration has primarily involved storm winds and earthquakes (Davidson, Liu, Sarpong, Sparks, & Rosowsky, 2003; Reed, 2008; Reed, Powell, & Westerman, 2010; Reed, Preuss, & Park, 2006). In addition to the intensity of weather events, however, Liu, Davidson, and Apanasovich (2007) note that the type of infrastructure (i.e. transmission lines, substations, protective

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devices, and service transformer) and environmental conditions (i.e. population density and land cover) are also important factors.

Aside from interactions between infrastructure and the environment, we focus on another dimension of the resilience of power distribution infrastructures that has largely escaped attention—namely, the spatial dependence of outages experienced by electricity consumers. Spatial dependence is the tendency of nearby locations to possess similar attributes (Goodchild, 1992). It occurs when measures of attributes are correlated over space on account of underlying spatial interactions. It has been applied to geographical analyses of health (Crighton, Elliott, Moineddin, Kanarogloub, & Upshur, 2007; Ha & Thill, 2011), crime (Wang & Arnold, 2008; Ye & Wu, 2011), non-market valuation (Can, 1992), knowledge networks (Anselin, Varga, & Acs, 1997; ÓhUallacháin & Leslie, 2005), economic development (Dall'erba & Le Gallo, 2008; Rey & Montouri, 1999), water consumption (Chang, Parandvash, & Shandas, 2010; Scott, Dall'erba, & Caravantes, 2010) and species habitat distribution (Gao & Li, 2011; Miller, 2006; Su, Jiang, Zhang, & Zhang, 2011).

To date there have been relatively little analyses of spatial dependence within infrastructure systems. Yet, we would expect to see spatial dependence both because of the structure of the network, because infrastructure–environmental interactions depend more on neighborhood than on individual residence characteristics, and because the speed of response to outages in any given area depends on the presence of particular types of consumer. To our knowledge, there is no outage duration model incorporating spatial dependence among consumers. But where spatial dependence exists, a spatial outage duration model is needed to produce unbiased and consistent parameter estimates. We investigated the relation between outage duration and proximity to locations that have the highest priority in power companies' response strategies. Where individual residences are located near high priority public facilities such as hospitals, for example, we found that they benefit from a triage process by power companies that privileges emergency services. That is, hospitals 'confer' resilience on the power distribution system in the immediate neighborhood. This aspect of the resilience of electrical power distribution systems has not previously been studied.

We modeled average outage duration across Phoenix, Arizona, between 2002 and 2005, using spatially explicit outage data provided by a local utility company. Outages are defined as all unscheduled incidents where voltage falls to zero. This includes momentary incidents persisting no longer than a few seconds and blackout incidents persisting longer than several minutes. We focus on the distribution system (the supply of low voltage electricity from distribution substations to end users) rather than the transmission system (the bulk supply of high voltage electricity from a generating source to distribution substations) since we are interested in residential power outage duration. Because the distribution system covers a greater geographical area than the transmission system, it also encompasses a wider variation of urban conditions, is more exposed to hazardous environmental events and conditions, and accounts for most of the interruptions experienced by electricity consumers (Brown, 2002; Pahwa, 2004). We modeled the effect of a variety of interacting environmental and infrastructural conditions on outage duration, including vegetation abundance, feeder type, age associated with feeder, demand for electricity, ambient temperature, the number of unscheduled outages, the number of customers affected by those outages, proximity to arterial roads, proximity to critical assets (i.e. hospitals), and proximity to the central business district (CBD).

Hypotheses

The resilience of any power distribution system, regardless of specific location, depends on a number of conditions. This allows us to construct a general model that can be applied to any urban electrical distribution system. Conceptually, outage duration depends on the following factors:

Physical characteristics

1) The nature of external shocks: the type and intensity of weather or other shocks is positively correlated with the extent of damage and hence repair times.
2) Prevailing environmental conditions: places with overhead lines that are more exposed to larger, heavier, and more abundant vegetation conditions will be most vulnerable to outages due to weather events.
3) Land use: dense areas may experience more outages or require longer restoration times due to congestion.
4) Infrastructural characteristics: the type of feeder (overhead or underground), its age, and whether a distribution system is looped (interconnected) or radial affects its vulnerability to weather shocks.

Triage characteristics

5) The number of customers affected: Electrical power utility companies will give restoration priority to outages affecting large numbers of customers.
6) Type of customers affected: Electrical power utility companies will give restoration priority to critical assets such as hospitals.
7) Access of utility repair trucks to outage location: locations closer to repair yards should experience shorter restoration times.

Factors 1, 2, 3 and 4 concern the severity of the event that is the proximate cause of the outage, and the importance of interactions between the power distribution infrastructure and environmental conditions. More severe events generally lead to more damage and hence longer repair times than less severe events. Similarly, some environmental conditions are expected to cause more damage to distribution equipment than others, having a larger impact on outage duration. For example, trees would be expected to lead to more damage to overhead equipment than birds simply because they are larger, heavier, and can move through interactions with wind and other wildlife as well as grow into conductors. Larger trees are also expected to be associated with higher levels of damage to overhead equipment than smaller trees.

Certain types of land use may be associated with longer restoration times. For example, some locations may require longer repair times due to inaccessibility. Extremely congested areas, for instance, can be difficult environments for repair crews to work in, owing to limited space.

Infrastructural characteristics involve the type and age of feeder lines, which are often assumed to prolong outages. First, underground cables may, on average, require longer restoration times than overhead lines due to the necessary time for repair crews to identify and reach underground outage sources and locations (Chow et al., 1996). However, underground cables are less prone to damage since they are sheltered from many environmental events and conditions. Second, older infrastructures are more vulnerable to failure and may need replacement during outage occurrences. Equipment replacement will require longer restoration times for necessary installation of new equipment. Finally, some electrical power distribution is looped or interconnected, allowing for rapid restoration through automated switching by utilities. This enables a re-route of electrical power in the case that one route fails

(Kersting, Phillips, & Doyle, 1999). In contrast, customers served through a radial configuration that are 'downstream' of an outage will incur downtime costs as repair crews repair/replace a failed component (see Fig. 1).

Factors 5, 6, and 7 are triage characteristics, meaning they concern response priorities and response capabilities. First, in the event of an outage, electrical utilities usually conduct a damage assessment that identifies the cause and location of outage, and how many customers are affected. Deregulated electric power providers have economic incentive to repair outages affecting more customers more quickly than outages affecting fewer customers because repairing outages affecting the most customers in the event of simultaneous outages will help minimize average system interruption times. Therefore, we expected that the number of customers affected by an outage would be positively correlated with the effort given to restoring the power supply.

The type of customer is also considered in the initial damage assessment. In the event of an outage, utilities give emergency assets such as hospitals priority over residential customers (Curcic, Ozveren, Crowe, & Lo, 1996). Hospitals will generally encounter shorter outage lengths than residential customers for two main reasons. First, hospitals are typically served by 'loop' rather than 'radial' lines, and this reduces the time of any outage. Electrical power supply can be re-routed through an undamaged feeder. Second, hospitals are high priority customers. If an outage occurs and affects power supplied to a hospital, that hospital will be given the highest priority by the utility. Although many hospitals have redundant power supplies such as back-up generators, electrical utility companies are still obligated to restore power to these customers first (Curcic et al., 1996). We test the hypothesis that houses closer to hospitals will benefit from the priority given to them. Residential customers located close to hospitals may experience shorter outages by being either connected to a looped feeder or by having repair crews restore power outward from a prior critical customer (i.e. a hospital). Consequently, proximity to emergency assets may confer outage resilience to residential customers.

Finally, after the initial damage investigation, utilities make repairs. Repair capability depends on access of utility repair trucks to outage locations and is ultimately important for restoration times. Outage locations that are farther away from repair deployment yards will, on average, have longer periods of outage due to the time necessary for maintenance crews to travel to the outage location.

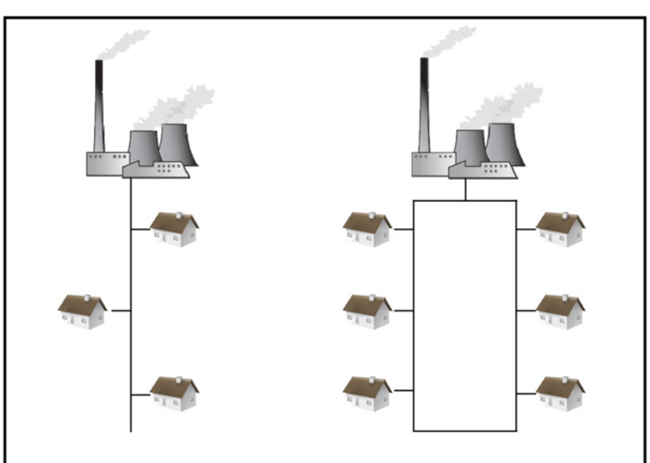

Fig. 1. Electrical feeder configurations. Radial (left) and looped (right).

Data and methods

Study area

We applied our modeling framework to a major urban area in the Southwestern United States. The study area for this research is a section of the City of Phoenix, Arizona. Phoenix is the sixth largest city in the U.S. and holds about 35% of the metropolitan area's population (U.S. Census Bureau, 2010). Electrical power is supplied to the area by two major utilities, Arizona Public Service (APS) and the Salt River Project (SRP). The study area falls within the part of Phoenix serviced by APS. Out of the 1,445,632 people in the City of Phoenix, APS covers roughly 746,187 people, or about 52% of the population according to the 2010 census. Fig. 2 shows the power distribution infrastructure of the study area in relation to the Phoenix Metropolitan Area.

Data

The purpose of modeling outage restoration times is to understand the determinants of electrical resilience. Our measure of the resilience of the electric power distribution system is the time to restoration of service following a failure within that system. Supply interruptions may occur when there is an outage in the generation, transmission, sub-transmission, or distribution system. We focused on the last of these. We included all reported unscheduled outages regardless of duration. These ranged from momentary incidents that persisted no longer than a few seconds to blackout incidents that lasted several hours. Outages were limited to those caused by failure of the electrical distribution system (the low voltage power supply system between distribution substations and end users) rather than the electrical transmission system (the high voltage power supply system between a generating source and distribution substations). Outages were then weighted by time in minutes.

Many environmental conditions potentially cause unscheduled residential power interruptions in Phoenix, and their effect varies depending on the configuration of the power distribution. Data on power line location, type (overhead or underground), outage duration, and number of customers affected for the period 2002–2005, were obtained from APS to examine the factors affecting average residential power outage duration. Feeder line types and locations are mapped in Fig. 2. It is clear from the map that roughly half the study area is served by overhead lines, the remaining area being served by underground cables. Causes of outages were grouped into the following categories: scheduled outages, accidental outages, and environmental outages (a subset of accidental outages). We focused on unscheduled (i.e. accidental and environmental) outages affecting single-family housing units.

Since our ultimate aim (not the aim of this paper) is to estimate the capitalized value of residential electrical power resilience through hedonic pricing methods, our sample was based on housing sale location data. Hedonic methods decompose a marketed item into a number of attributes over which purchasers have preferences. By estimating a hedonic price function it is possible to infer purchasers' marginal willingness to pay (MWTP) for each attribute. For instance, house prices can be used to infer the value of a public service by estimating the MWTP for that service, controlling for salient housing characteristics, neighborhood characteristics, and other environmental characteristics. House sale data were obtained from the Maricopa County Assessor's Office (MCAO) for the year 2005 to account for the period of observed outages. This yielded 6061 housing observations. We linked the number of outages and total duration per house location sale by feeder type. This was done by having each housing sale location assigned to its

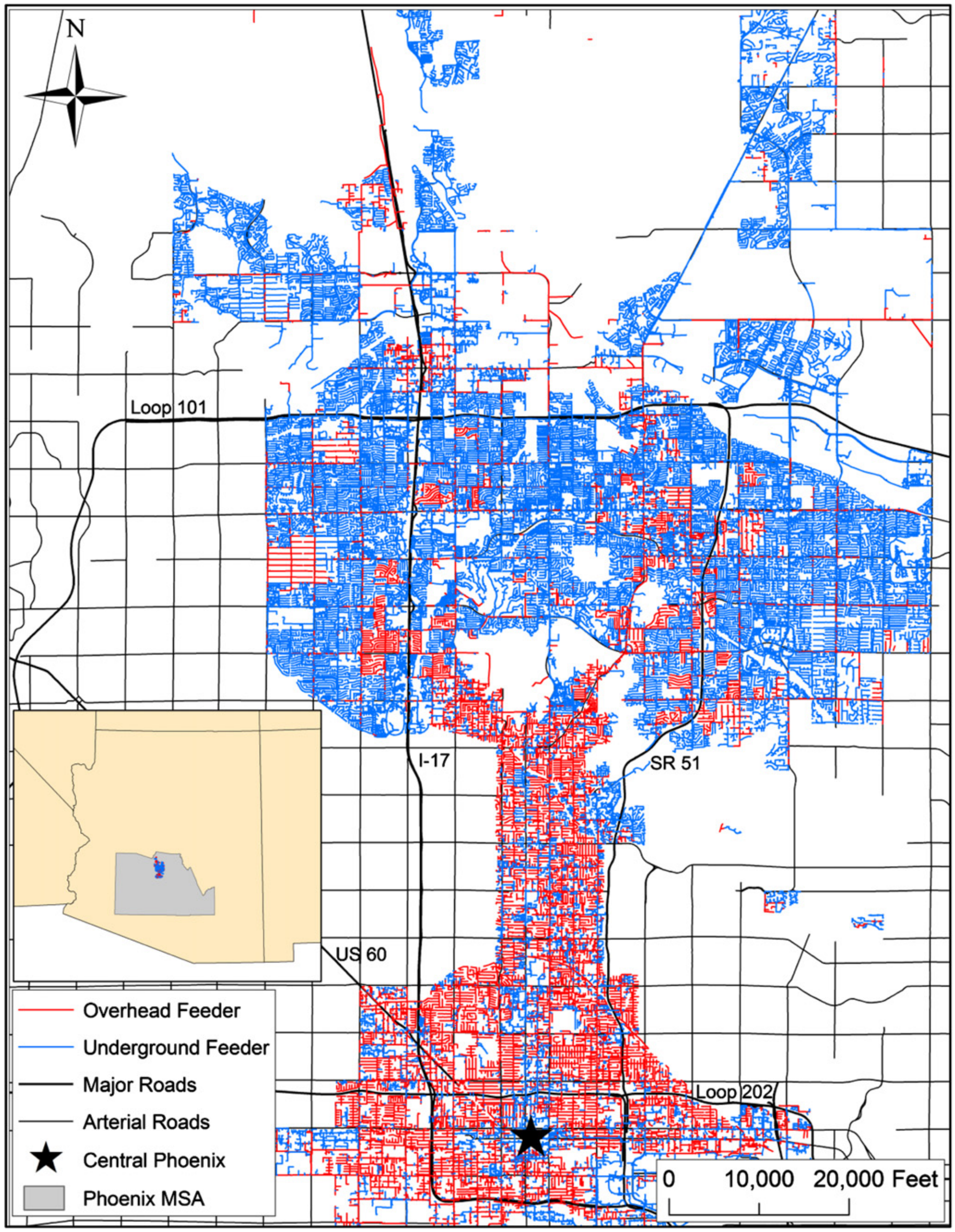

Fig. 2. Map of study area and feeder types.

nearest feeder line. We also used the MCAO database of parcels to determine the construction year for each house to serve as a proxy for infrastructure age. Fig. 3 shows the distribution of average duration of unscheduled outages (in minutes) from 2002 to 2005 across the study area. Fig. 4 shows the distribution of the average number of customers affected per outage between 2002 and 2005. Fig. 5 shows the number of unscheduled outages from 2002 to 2005 at each house sale location in 2005.

We obtained further characteristics of houses that might affect outage duration comprising several proximity variables to other features including distance to nearest hospital, distance to nearest arterial road, distance to nearest native desert area, and distance to the CBD. These variables were constructed by measuring Euclidean (straight line) distances in feet from the centroid (geometric center) of each parcel to the nearest feature of interest. Fig. 6 shows the proximity of each 2005 house sale to its nearest hospital.

Other environmental variables relevant to Phoenix residents include vegetation and bird abundance, as well as ambient temperatures. The Soil Adjusted Vegetation Index (SAVI) was used as a proxy for vegetation abundance and was derived from a 2005 Landsat Thematic Mapper (ETM) image. It was obtained through the Central Arizona Phoenix Long Term Ecological Research (CAP-LTER) project. CAP-LTER is a nationally funded project to study the long-term ecological sustainability of cities. Fig. 7 shows the distribution of vegetation across the study area. Bird abundance data were also obtained through CAP-LTER. These data were collected by monitoring birds seasonally across 40 sites from 2002 to 2004. Counts were then interpolated over the entire metropolitan area (see Walker et al., 2008 for methodological details).

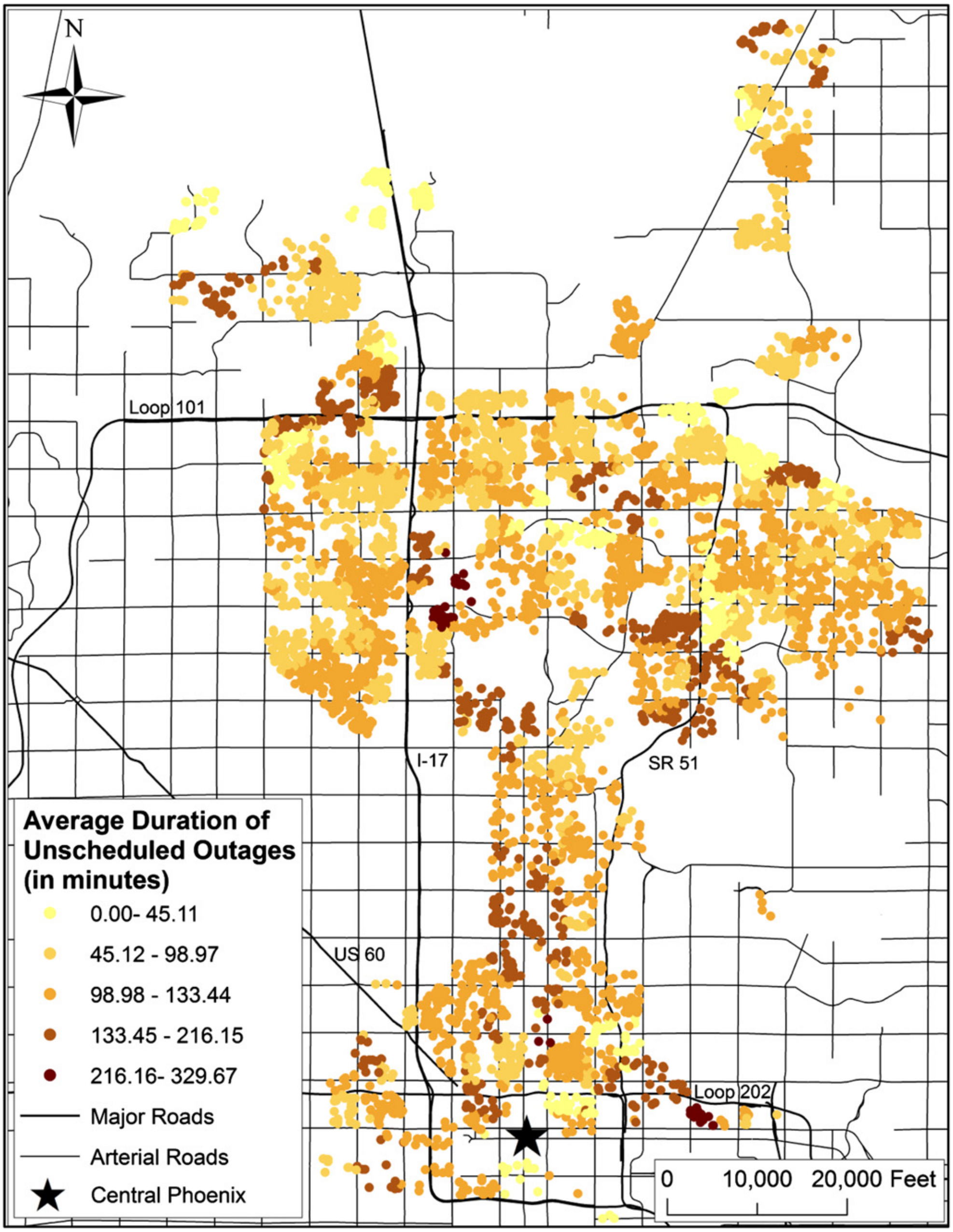

Fig. 3. Map of average outage duration times (in minutes) from 2002 to 2005. Colored symbols classified in natural breaks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

August minimum temperature in Celsius was used as a proxy for Phoenix's urban heat island (UHI), and more generally ambient temperature. In the Phoenix metropolitan area, the UHI effect is observed in the elevation of night-time temperatures and is most strongly observed in the summer months (Baker et al., 2002), thus mean August minima are appropriate indicators. These data were also obtained through CAP-LTER and were derived from spatial interpolation of daily temperature data from 55 meteorological sensors from different sources including the Flood Control District of Maricopa County (ALERT), the National Weather Service (NWS), the Arizona Meteorological Network (AZMET), and the Phoenix Real-time Instrumentation for Surface Meteorological Studies (PRISMS) Network. Daily measurements were aggregated to bi-weekly periods. Variable names, descriptions, and statistics are provided in Table 1.

Model

Average duration of unscheduled outages was hypothesized to depend on a set of infrastructural conditions, environmental conditions, and triage characteristics. The infrastructural conditions included infrastructure type, age, and location. The environmental conditions included temperature, vegetation, bird abundance, and proximity to desert. The triage characteristics included the number of unscheduled outages, the number of customers affected, and the types of customers affected. Access to repair depots (in terms of distance) was excluded from the analysis because data on the locations of repair depots are confidential. We estimated a model of the following general functional form:

$$y_i = f(d_i, \mathbf{o}_i, \mathbf{x}_i, \mathbf{z}_i) + \varepsilon_i \tag{1}$$

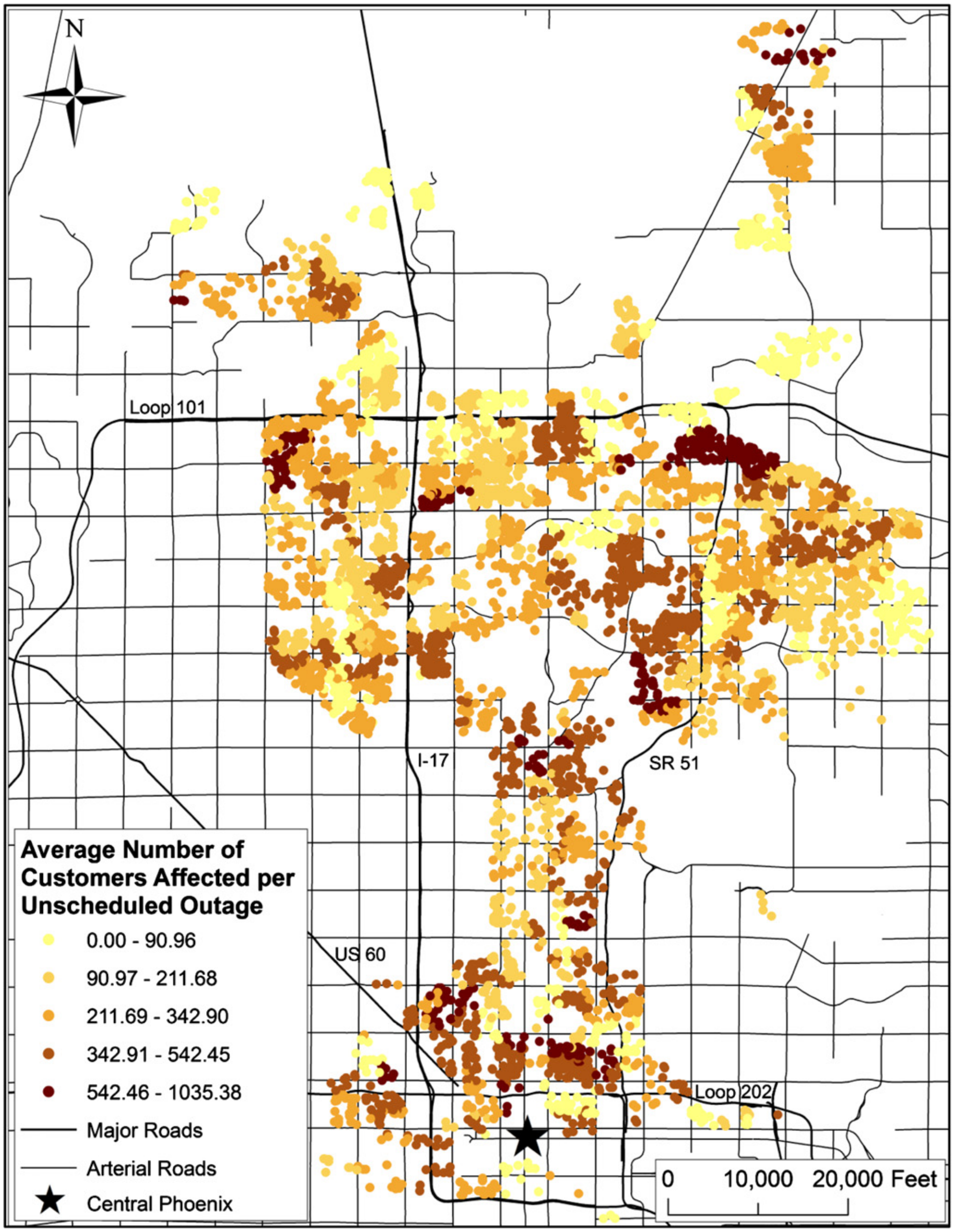

Fig. 4. Map of average number of customers affected per unscheduled outage from 2002 to 2005. Colored symbols classified in natural breaks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

where i is an index of locations, y is the average duration of unscheduled outages, d is the demand for energy, $\mathbf{o}$ is a vector of associated triage characteristics, $\mathbf{x}$ is a vector of associated infrastructural conditions, $\mathbf{z}$ is a vector of associated environmental conditions, and ε_i is an error term.

The outage duration model was empirically calibrated for Phoenix, Arizona, but the general form could readily be applied to other urban areas. Given that our study area is constrained to Phoenix, its desert conditions helped guide our selection of infrastructural and environmental variables affecting power distribution reliability. In this case, infrastructural conditions comprised the type of power distribution infrastructure, and its location with respect to other major built infrastructures such as arterial roads. That is:

X = (feeder type, proximity to arterial road).

The outage characteristics comprised the number of unscheduled outages experienced, the number of customers affected, and the type of customers affected. That is:

$\mathbf{o}$ = (number of outages, number of customers affected, type of customers affected).

The environmental conditions were captured by measures of species abundance, climatic conditions and distance from the desert. That is:

$\mathbf{z}$ = (vegetation abundance, bird abundance, proximity to desert).

The estimated model is:

$$y_i = a + \beta_d d_i + \sum_j \beta_j o_{ij} + \sum_j \beta_j x_{ij} + \sum_j \beta_j z_{ij} + \varepsilon_i \tag{2}$$

where

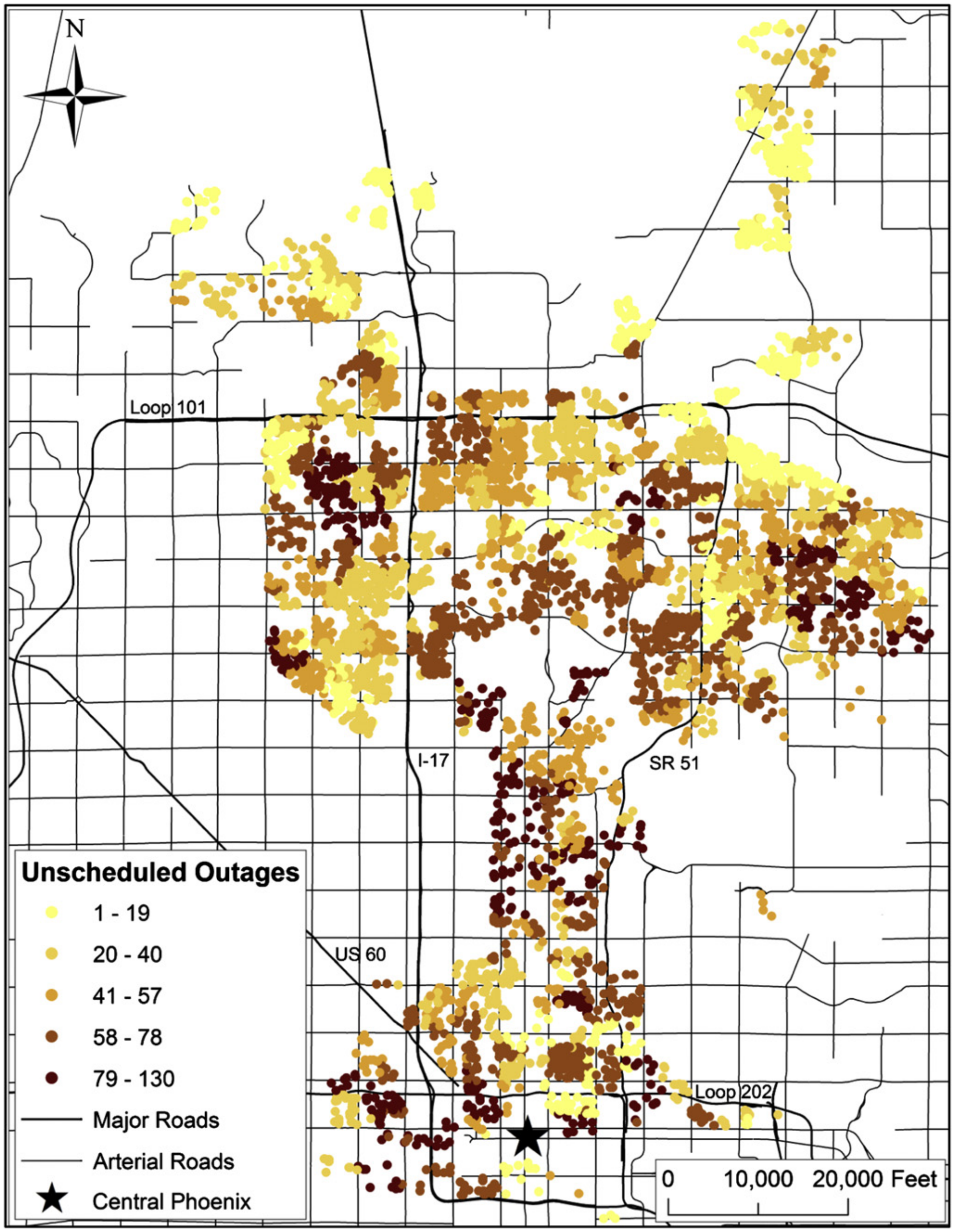

Fig. 5. Map of number of unscheduled outages from 2002 to 2005. Colored symbols classified in natural breaks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

$$\sum_j \beta_j o_j = \beta_{OUT}OUT + \beta_{CUST}CUST + \beta_{HOSP}HOSP \tag{3}$$

and

$$\sum_j \beta_j x_j = \beta_{OH}OH + \beta_{ART}ART \tag{4}$$

and

$$\sum_j \beta_j z_j = \beta_{BIRD}BIRD + \beta_{VEG}VEG + \beta_{DES}DES \tag{5}$$

in which the variables are described in Table 1. We expected to find significant interactions between the environmental variables and the type and/or age of infrastructure. The interaction between the environmental variables and overhead lines is straightforward—weather conditions frequently affect overhead lines via the impact they have on vegetation. We expected interaction terms between those variables to have a positive effect on outage duration. Vegetation, especially large 'danger trees' (trees outside a right-of-way that can fall within five feet of a distribution line, (Tennessee Valley Authority, 2011)) may potentially interfere with overhead distribution equipment. Together with overhead distribution lines, heavily vegetated areas are more likely to experience outages than areas with underground cables or fewer trees.

Temperature events (especially periods of excessive heat) are expected to induce outages through demand spikes. To capture this we included an interaction between housing square footage and temperature. Square footage or temperature may be main effects. The interaction between them is a way of weighting temperature.

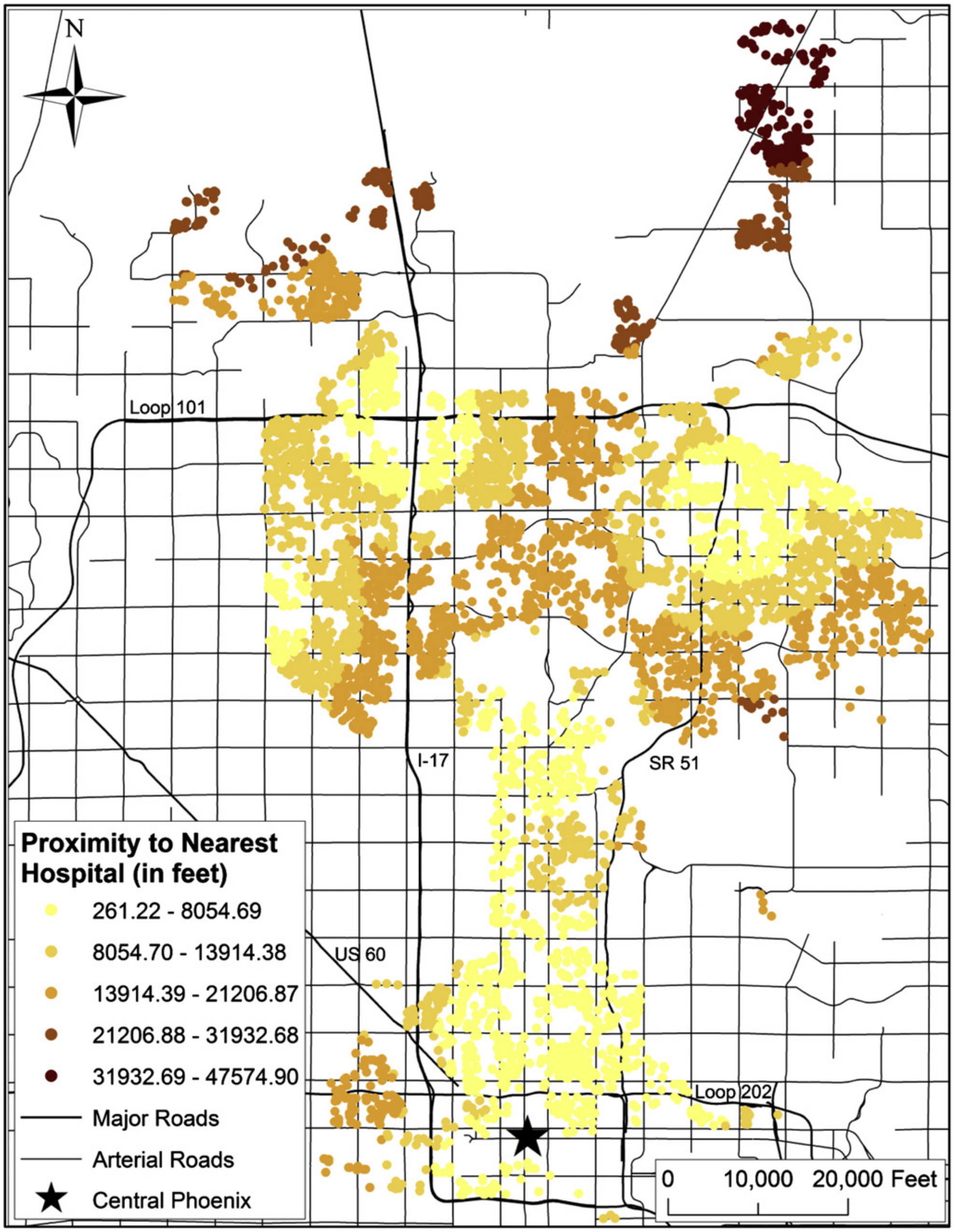

Fig. 6. Map of proximity to nearest hospital (in feet). Colored symbols classified in natural breaks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This is simply because larger houses require more energy to cool the living areas. Given these considerations, we also estimate an interaction model of the form:

$$y_i = a + \sum_j \beta_j z_{ij} d_i + \sum_j \beta_j o_{ij} + \sum_j \beta_j x_{ij} + \sum_j \beta_j z_{ij} + \sum_j \beta_j x_{ij} o_{ij} + \sum_j \beta_j x_{ij} z_{ij} + \varepsilon \quad (6)$$

where

$$\sum_j \beta_j z_{ij} d_i = \beta_{SQFT*TEMP}(SQFT*TEMP) \quad (7)$$

and

$$\sum_j \beta_j x_{ij} z_{ij} = \beta_{BVOH}(BIRD*VEG*OH) + \beta_{DESOH}(DES*OH) \quad (8)$$

We estimated the model with ordinary least squares (OLS). A potentially important issue to be addressed in the estimation of this model is the likelihood that an interruption at one house is dependent on an outage at a nearby feeder. This gives rise to the possibility that outages in a neighborhood supplied by the same feeder or experiencing the same environmental conditions will experience the same or similar duration of interruption. They will be spatially correlated. However, we expect that the degree of spatial correlation will be different in cases where power distribution systems rely on radial and looped systems of energy distribution (Perrier et al., 2010; Willis, Welch, & Schrieber, 2001). Radial distributions provide energy to customers directly from

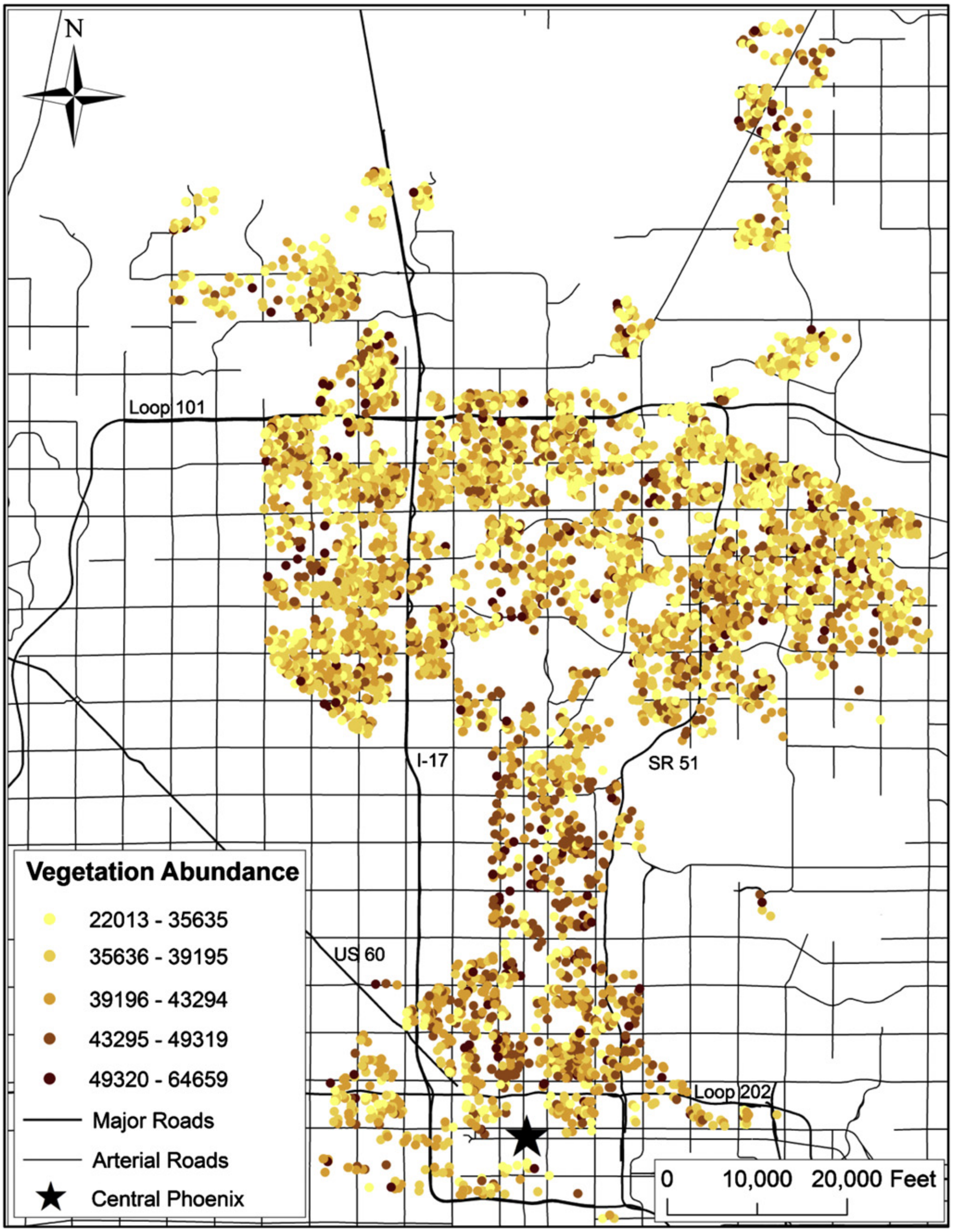

Fig. 7. Map of vegetation abundance per house sale in 2005. Colored symbols classified in natural breaks. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

a transformer to nearby end users whereas looped distribution systems are interconnected, allowing for back-end power supply routes in case a component fails. The weakness of a radial distribution system is that any residence that is 'downstream' of a failure will also experience an interruption.

In reality, houses are dependent on the reliability of the feeder rather than a neighboring house. However, since we assign houses to their closest feeder, this is formally equivalent to spatial dependence between the reliability experienced by different houses served by the same feeder. Furthermore, neighborhoods containing many houses will have similar biophysical environments suggesting houses exposed to environmental conditions such as birds, vegetation, overhead lines, or desert conditions will experience a similar effect. Hence, it is still reasonable to explore the spatial correlation between average duration of unscheduled outages in neighboring locations.

Spatial dependence can generally take two forms. First, it can result from underlying spatial interactions. In the case of electrical power supply, an outage at one house would not cause an outage at another house. Therefore, spatially lagged dependence is conceptually not applicable. The spatial relationship of reliability among neighboring houses is a spatial association of a second kind, i.e. spatial dependence can result from misspecification in the form of omitted variables, incorrect functional specification, or measurement error. We ran spatial diagnostic tests to determine whether spatial lag dependence or spatial error dependence should be controlled for in the model before coefficient estimation. The spatial diagnostic tests were based on a Moran's *I* analysis of the OLS residuals and Lagrange Multiplier methods detailed in Anselin, Bera, Florax, and Yoon (1996). As expected, spatial diagnostic tests indicated spatial dependence to be a result of spatial measurement

Table 1
Names, descriptions, and basic statistics of variables ($n = 6061$).

Name	Description	Mean	SD	Min	Max
TIME	Average duration of unscheduled outages (minutes)	99.32	42.91	0	329.7
OUT	Number of unscheduled outages	44.94	26.82	1	130
CUST	Average number of customers affected per unscheduled outage	267	184.44	0	1035
OH	% houses in tract supplied by overhead feeder	0.26	0.36	0	1
UG	% of houses in tract supplied by underground feeder	0.74	0.36	0	1
SQFT	Housing area (sq. ft.)	1681.81	581.28	445	5360
ART	Distance to nearest arterial road (ft.)	1031.42	775.86	0.58	6924.81
VEG	Vegetation abundance; Soil-Adjusted Vegetation Index	39297.06	4764.78	22013	64659
BIRD	Bird abundance	129.98	18.30	78	169
DES	Distance to nearest desert area (ft.)	5727	4373.79	34.73	20672.30
AGE	Proximate age of infrastructure (yrs.)	27.80	18.84	1	105
LAKE	Distance to nearest lake (ft.)	5168.50	3039.63	192	19623.70
PHX	Distance to center city (ft.)	66014	26324.91	1906	125204
HOSP	Distance to nearest hospital (ft.)	12470	7512.08	261.2	47570
TEMP	August minimum temperature (Celsius)	21	0.14	20	22

error rather than spatial externalities. We accordingly estimated a spatial error model of the following form:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \lambda\mathbf{W}\mathbf{u} + \mathbf{e} \tag{9}$$

in which $\mathbf{y}$ is a vector of observations on the dependent variable, $\mathbf{X}$ is a matrix of observations on the independent variables, $\boldsymbol{\beta}$ is a vector of regression coefficients to be estimated, $\mathbf{u}$ is a vector of spatially autocorrelated error terms, λ is a coefficient to be estimated, and $\mathbf{e}$ is a vector of error terms. The spatial weights matrix $\mathbf{W}$ contains binary elements such that $w_{ij} = 1$ if houses i and j are considered neighbors, 0 if not, and i not equal to j. The spatial weights can be constructed in different ways. We chose to use a distance band comprising the distance limit from which a feeder provides electricity to nearby houses. We tested a range of distance bands. At one extreme, the spatial weights matrix defined neighbors on the basis of a minimum Euclidean distance threshold such that each house had at least one neighbor. This resulted in each house sale within 3760 feet from sale location i as a neighbor. At the other extreme, every house within a distance radius of 500 feet of house i was considered a neighbor. Based on a Moran's I analysis, the most suitable representative supply range appeared to be somewhere in between 800 and 1200 feet.

An issue in estimating the coefficients in a spatial regression model is that since spatially lagged variables are endogenous they need to be instrumented on the relevant exogenous variables (Anselin, 2002). We estimated these coefficients using the Maximum Likelihood Estimation method in GeoDa™ (Anselin, Syabri, & Kho, 2006).

Results

Coefficient estimates for the non-spatial and spatial outage duration models are reported in Table 2. The overall fit for the non-spatial model was reasonable (adjusted $R^2 = 0.382$). Diagnostics revealed low multicollinearity (Multicollinearity Condition

Table 2
Outage duration model results ($n = 6061$).

Name	Non-spatial (OLS)		Spatial (1000 feet)	
	Coefficient	t	Coefficient	z
(Constant)	2.859E+1	12.631	31.768	8.858
*SQFT*TEMP*	2.315E-4	5.714	4.363E-5	1.775
*VEG*OH*	5.849E−4	15.152	4.545E-4	7.657
ART	9.729E-4	1.691	3.649E-4	0.538
HOSP	6.974E-4	9.104	7.526E-4	4.942
PHX/AGE	−3.374E-4	−4.091	−1.750E−4	−2.564
DES	−5.684E-4	−4.625	1.405E-3	5.732
OUT	2.332	45.644	2.172	43.653
OUT^2	−1.550E-2	−32.775	−1.400E−2	−31.889
CUST	−4.318E−2	−14.453	−5.296E−2	−18.322
CUST/HOSP	2.612E+1	2.393	6.497	5.448
λ	–	–	8.674E-1	178.796
Adj. R^2	0.382	–	–	–
Pseudo R^2	–	–	–	0.868
MCN	21.571	–	–	–

Note: MCN represents Multicollinearity Condition Number.

Number = 21.571) but indicated severe spatial dependence. Table 2 also provides coefficient estimates for each of the outage factors in a spatial error model with neighbors defined on the basis of observed houses within 1000 feet from observed house location i. The pseudo- R^2 value for the spatial error model was 0.868—a substantial improvement over the non-spatial model. The coefficient for the spatial error term was positive and highly significant.

In the non-spatial model, the most significant factor explaining the duration of unscheduled outages was the total number of unscheduled outages. However, the relationship between number of outages and average outage duration was not linear. A scatterplot visualization between number of unscheduled outages and average duration of outages shows a steep increase in average duration up to about 40 outages. After that, the slope significantly decreases but remains positive. This might be explained by the difference in infrastructural and environmental conditions corresponding to observations above and below 40 outages. The variation in infrastructural and locational characteristics in houses experiencing more than 40 outages was relatively small, since these areas are served primarily by overhead lines. By contrast the differences in infrastructural characteristics and locational characteristics in houses experiencing less than 40 outages were much larger.

We found the interaction between vegetation abundance and overhead distribution lines to be positively and significantly related to the average duration of an outage. Consistent with our expectation that proximity to high priority public facilities confers resilience on neighboring infrastructures, we found that distance from the nearest hospital was positive and highly significantly related to outage duration. That is, houses closer to hospitals are likely to have their power restored much more quickly than houses farther away from hospitals.

Also consistent with our expectations, we found that the number of customers affected per outage reduces the average duration of an outage. An interaction term between proximity to the nearest hospital and number of customers affected was also significantly related to outage duration, meaning locations with fewer customers affected and relatively far from hospitals tend to have longer outage durations. The interaction between housing square footage and ambient temperature was positive and significant, indicating greater energy demand increases the average duration of outages. Finally, an interaction between distance to the CBD and the age of infrastructures was also significantly related to outage duration. The coefficient on the distance to the nearest arterial road was positive and marginally significant, indicating outage locations farther from arterial roads tend to have longer durations than outage locations closer to arterial roads. The coefficient for distance to the nearest native desert area was negative and significant implying outage locations close to desert areas on average tend to have longer outage durations than areas farther away from desert areas.

For the spatial error model, the interpretation was broadly similar. However, we found that the 'distance' measures used in the non-spatial model changed. The coefficient on distance to the nearest arterial road became insignificant, and the coefficient for distance to the nearest desert area switched in sign while remaining significant. Both effects may reflect collinearity between the distance measures used and the spatial weights in **W**. Lastly, the significance of our proxy for energy demand (the interaction between house size and temperature) was reduced. At the same time, the coefficient for spatial dependence turned out to be positive and highly significant, indicating that houses in the same neighborhood (within 1000 feet) are likely to experience very similar duration per electrical power interruption.

Discussion and conclusions

There is a general consensus in the literature that the factors affecting the number of power outages also affect their duration. In particular, the extent of the damage caused is positively correlated with the length of time it takes to repair that damage. This reflects both the severity of the weather (or other) event that is the proximate cause of an outage, and the vulnerability or robustness of the infrastructure. The vulnerability of infrastructure is related both to its type and its age. We found that the age and type of infrastructure interacts with environmental conditions and environmental events to explain the duration of outages. This appears to be particularly true for vegetation abundance. This may be because vegetation causes more damage than other environmental variables such as birds. The latter are significant source of outages, but do not explain outage duration. Proximity to the CBD is also highly correlated with both age and infrastructure type. Specifically, overhead lines are more frequently found close to central Phoenix, and are older than other lines. Contrary to expectation, we found that the duration of outages in areas served by underground lines was shorter than in areas served by overhead lines.

What we found that has not previously been noted in the literature is the degree to which proximity to high priority public services such as hospitals confers resilience on the neighboring infrastructure. We have noted that the resilience of infrastructures depends both on the physical characteristics of the power distribution network, and on the effectiveness of network management. In particular, the time to restoration of power supplies depends on the resources committed by the electricity supply company. This generally reflects a triage that takes into account both the number and type of customers affected. Outages that impact large numbers of people or high priority public services attract attention over sparse residential areas. Residential areas in the neighborhood of high priority users benefit from a positive externality conferred both by the quality of infrastructure provided and the priority given to restoring supply to those users. Our findings suggest that utility companies give greater priority to both critical customers and a large number of customers. It is worth noting, though, that not all public facilities confer resilience on neighboring areas. We also tested the importance of proximity to police stations, fire stations and schools. All turned out either to be insignificant or to have a negative relation to outage duration. Data that would be useful in further research include the spatial footprint and intensity of weather events (since many of these are quite localized), and the locations of utility repair depots (since these may help explain response/restoration times).

Finally, we found that incorporating a spatial error term improves the model fit substantially (by 227%). While a non-spatial outage duration model provides insight into the main factors affecting the resilience of infrastructures, the coefficient estimates are inconsistent by the high spatial dependence among outage durations. The spatial model provides additional information on the degree to which neighboring houses endure similar outages. We found that spatial associations are strongest between 800 and 1200 feet with spatial associations decreasing with increases in distance over 1200 feet. To our knowledge, this is the first study to explore the effect of interactions between environmental, infrastructural, and social conditions on the resilience of power distribution networks accounting for spatial dependence among residential properties. These findings are important for both understanding the resilience of electrical power distribution systems, and for future energy resilience planning.

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