Resilience of Energy Systems:

Theoretical and Empirical Perspectives

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Abstract

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The ability to absorb, adapt, and recover from disruptions – also termed resilience – is a beneficial characteristic of any natural or anthropogenic system, including energy systems, that are exposed to natural hazards. Energy systems that supply us with fuel and electricity are essential for the health and prosperity of most communities around the world. Increasing the resilience of these systems and, thereby, minimizing disruption in critical services, such as telecommunications and water treatment, is an often stated goal of policy makers, regulators, and utilities. This goal, however, has proven difficult to achieve due to a lack of standardized resilience practices. The research presented in this dissertation develops a measurement framework that can inform the development of analytical models and develops two analytical models that examine the resilience of electric power systems using empirical data. Broadly, the research presented in this dissertation contributes to the fields of disaster management and energy systems in relation to vulnerability, risk, and resilience by examining theoretical perspectives and testing analytical methodologies with empirical power outage data. The findings of this dissertation will hopefully facilitate the development of energy system planning and management approaches that incorporate resilience as a key principle rather than regulatory jargon.

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Chapter One

Introduction

The inability of electric power systems to adequately withstand natural hazards, such as hurricanes and flood events, has significant impacts on society. Power outages cost the U.S. economy billions of dollars each year in lost output and wages, spoilage, delayed production, inconvenience, property damage, and grid damage (EOP 2013; DOE 2016). Lost economic production is often accompanied by the loss of critical health services, such as potable water, emergency communication/transport, and medical life support capabilities. Such hazards become increasingly problematic when there are meaningful human impacts. Hazards can cause physical injuries, illness, emotional distress, loss of life, and property damage. The same hazard – in terms of frequency, duration, and magnitude – can affect people and communities differently depending on their respective social vulnerability.

Traditionally, practitioners have used risk-based approaches to examine the impacts of adverse events to energy systems. While closely related, resilience examines the ability of a system to recover from an adverse event, whereas risk strictly examines the losses or harm due to an adverse event. More specifically, resilience focuses on functional performance and risk focuses on damage (Ganin et al. 2016; Schultz and Smith 2016). By examining system functionality over time, resilience can identify critical services or tasks that the system provides to stakeholders. Resilience, therefore, incorporates a temporal dimension that is often lacking in risk-based approaches (Linkov et al. 2014).

As decentralized energy resources and services continue to expand across the electric grid, geography will play an increasingly important role in planning and management activities. To date, however, resilience studies that examine electric power systems have largely overlooked the importance of geography and other spatial considerations. Practitioners must now plan for and manage a wider range of hazards that could impact decentralized systems, including distributed energy resources (e.g. microgrids), battery storage, and electric vehicles (EPRI 2016; Vugrin, Castillo, and Silva-Monry 2017). It is critical to understand how the spatial dimensions of electric power systems and the associated landscape link to resilience practices (Calvert 2015).

This dissertation examines the resilience of energy systems from both a theoretical and empirical perspective. The intended purpose is to study resilience from a geographic perspective, where the spatial activities and relationships associated with energy landscapes are a point of emphasis. There are three primary research objectives: 1) develop a resilience measurement framework that informs analytical models, 2) model electric power system performance in space and time, and 3) to analyze the relationship between electric power system performance and social vulnerability. A combination of qualitative and quantitative methods are used to accomplish these objectives. Each research objective is structured around a standalone manuscript. As such, Chapters 2, 3, and 4 form the main body of the dissertation as well as constitute the three standalone manuscripts. Chapter 5 provides concluding remarks and discusses the knowledge contribution of this dissertation as well as next research steps.

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Chapter Two

Resilience of Energy Systems:

A Resilience Measurement Framework and Literature Synthesis

1. Introduction

Energy systems face numerous economic, technical, and socio-political challenges. They must reliably and cost effectively deliver electricity and fuel to geographically dispersed consumers on a continuous basis. Under normal operating conditions, utilities and other parties that operate electric power systems must meet stringent requirements set forth by regulatory authorities that oversee electric generation, transmission, and distribution. Responsibilities include providing uninterruptable power supply, maintaining power quality, and providing frequency regulation services (De Martini 2014; EPRI 2013). Electric power and fuel are essential for all critical services and infrastructures, including emergency management, telecommunication, and water supply. The continued digitalization of our society, from wireless communications to automated home systems, has only increased reliance on electricity. This can cause extreme customer sensitivity to even minor power outages (EPRI 2013, 2016; DOE 2016).

These challenges are magnified when energy systems are exposed to both natural and man-made hazards, such as extreme weather events and cyber-attacks (EPRI 2016). Low probability, high consequence events that are largely unpredictable make energy systems vulnerable to severe disruptions in service, whether that is providing electricity to customers or delivering crude oil and natural gas to refineries (Vugrin, Castillo, and Silva-Monry 2017). Nonetheless, we expect these energy infrastructure systems to withstand and recover from hazards of a certain magnitude and maintain functional performance over time. This is termed resilience. More specifically, a resilient system is one that can absorb, adapt, and recover from disruptions by hazards (often called stressors) while still maintaining a specific function to meet certain livelihood needs (B. Walker and Salt 2012).

The need for resilient energy systems has been most dramatically emphasized by recent events in Puerto Rico, where Hurricanes Irma and Maria devastated the island's electric power system. Fifty percent of households were without power for over two months. Some residents were without power for over nine months (Toussie et al. 2018). Energy systems can face numerous operational and infrastructure challenges, including a small overall generation capacity compared to peak demand, low efficiency, and outdated generation and transmission/distribution equipment (Ochs et al. 2015). This often leads to electric grid reliability and stability issues, whereby the electric utility or utilities cannot adequately meet consumer demand (Bunker et al. 2015). These problems further compound the vulnerability of the energy infrastructure to natural hazards. Intense winds, high storm surges, and widespread flooding, all characteristics of severe weather events, can easily disrupt electric services for days, weeks, and even months.

Resilience is a complex notion rooted in the fields of economics, ecology, engineering, psychology, and sociology. Many of its foundational concepts can be traced to C.S. Holling's research on systems ecology. In one of his seminal publications, he defines resilience as the ability of a system to absorb change and still persist (Holling 1973). Holling further observes that traditional views of natural systems are not based in reality because "An equilibrium centered view is essentially static and provides little insight" (Holling 1973: 2). Since this 1973 publication, a new paradigm for ecological and social research has developed. Scholars view our world as inextricably linked social-ecological systems (SES). These SESs are dominated by nonlinear dynamics, feedback responses, thresholds, adaptive cycles, and cross-scale linkages (Gunderson and Holling 2002; B. Walker and Salt 2012).

Resilience, as applied to energy systems, is just now emerging as a prominent field of study. Over the last decade, researchers have proposed many different conceptual frameworks and metrics for analyzing energy system resilience. This includes work by academic institutions, government agencies and research laboratories, think tanks, non-profit organizations, and industry groups (Bruneau et al. 2003; Roege et al. 2014; Davidson et al. 2016; DOE 2016; Espinoza et al. 2016; Ganin et al. 2016; Kwasinski 2016; Schultz and Smith 2016; Panteli, Mancarella, and Trakas 2017; Vugrin, Castillo, and Silva-Monry 2017). Key components of this research include identifying specific hazards to the energy system, assessing system vulnerabilities, determining management goals and objectives, and evaluating resilience strategies.

A systematic framework for measuring resilience of infrastructure can assist with planning, design, implementation and monitoring of resilient infrastructures. This is particularly important since today's energy systems, especially with the integration of distributed energy resources, can operate at a wide range of technical and geographic scales (De Martini 2014). Unlike centralized thermal generation resources, distributed renewable energy resources are highly variable in space and time, even within a small geographic area. Energy systems are also intricately connected to the biophysical and socio-economic landscape. In addition, energy systems are especially vulnerable to long term hazards caused by climate change. This includes a shift in extreme weather events, changes in water availability, unusual seasonal temperatures, and rising sea level (IEA 2015; DOE 2016). Any energy transition, therefore, is a complex planning challenge that involves reconfiguring spatial activities, relationships, and infrastructure assets over long-term planning horizons. Such transitions are defined by ecologic, social, economic, and political relationships at multiple scales, including resource availability, utility ownership, and institutional arrangements. Currently, the world energy sector is undergoing a clean or green energy transitions, whereby fossil fuels are being replaced with low or zero carbon energy resources. Understanding how to assess and measure resilience is a step toward successful energy transition planning and management (Bridge et al. 2013; de Boer and Zuidema 2015; Calvert 2015).

This paper provides a detailed investigation into the resilience of electric power systems. This analysis broadly focuses on research literature that is connected to power systems resilience, including infrastructure, hazards, and emergency management research. The primary objectives of this paper are to 1) examine resilience as generally applied to electric power systems in order to identify key concepts; 2) explore how these resilience concepts are operationalized and applied in practice; and 3) develop a resilience measurement framework that informs more specialized analytical models as well as project planning and implementation.

2. Methods

The literature analysis and concept synthesis used to develop the resilience measurement framework was conducted using keyword searches (resilience AND: energy systems, power systems, electric power systems, electric grid, utility grid, or natural hazards) on Web of Science and ScienceDirect during May - December 2018. In addition, a Google Web Search was conducted to identify government, non-profit, and consultancy publications. This content analysis focused on publications that discuss resilience metrics, frameworks, or use a quantitative model to measure resilience in relation to electric power systems or energy systems more broadly. Publications that examine the general theory of resilience are also included to provide background and context.

Text from these documents is analyzed for specific concepts relevant to the main research objectives. Concepts and definitions are compared against each other throughout the research process to identify key themes relating to energy system resilience. This is an iterative process, whereby new concepts are examined in relation to ones that have previously appeared in the literature. The concepts are then linked together around central theories that are used to describe energy system resilience (Yin 2014). Section 3 presents the results of the literature analysis and discusses the overall development of the Resilience Measurement Framework used to synthesize the foundational concepts of energy system resilience.

3. Resilience Measurement Framework for Electric Power Systems

Table 1 presents a framework for investigating resilience, as specifically applied to electrical power systems. This study identifies four concepts critical to examining and measuring resilience: resilience principles, functional performance, resilience strategy, and scale of action. *Resilience principles* are the foundational elements of the system to achieve overall resilience. The "4 R's" of resilience – robustness, redundancy, resourcefulness, and rapidity – are commonly cited in natural hazard research as management components for critical infrastructure (Bruneau et al. 2003; Panteli and Mancarella 2015). *Functional performance* is the desired service activity of the system. Examples of functional performance include maintaining the structural integrity of infrastructure assets and reducing outage times (Ganin et al. 2016; Schultz and Smith 2016). Functional performance is further defined by metrics, objectives, thresholds, and goals. Together they provide a quantitative characterization of functional performance, such as the percentage of residents with electricity. Above a certain threshold, as defined by the resilience principle and quantified by a metric, functional performance is met and, therefore, the system is 'satisfactorily' resilient (Schultz and Smith 2016). *Resilience strategies* are actions that can harden the infrastructure from disturbance (e.g. placing distribution lines underground) or increase the operational capacity of the power system to manage a disturbance (e.g. advanced loading switching and balancing controls) (EPRI 2016). Finally, the *scale of action* is the geographic scale at which electric power resources are managed. These include the asset, service area, and system scales. Each scale is associated with a set of 4 R's.

Table 1: Resilience Measurement Framework

Resilience Principle	Functional Performance				Resilience Strategy	
	Metric	*Objective*	*Threshold*	*Goal*	*Hardening*	*Operational*
Asset Scale						
Robustness						
Redundancy						
Resourcefulness						
Rapidity						
Service Area Scale						
Robustness						
Redundancy						
Resourcefulness						
Rapidity						
System Scale						
Robustness						
Redundancy						
Resourcefulness						
Rapidity						

Table 2 organizes the resilience research literature according to the resilience concepts examined in this paper. For this table, only publications that directly address energy system or electric power system resilience are included. Each field contains the relevant citation(s). In some cases, the resilience concept was only implicitly discussed in the text but examined in enough detail to warrant inclusion. Scale of action, however, is not included in Table 2. Because scale is so rarely and often inadequately addressed, too many assumptions are needed to accurately infer which scale of action the publication is addressing.

Table 2: Modified Resilience Measurement Framework with Citations

Resilience Principle	Functional Performance				Resilience Strategy	
	Metric	*Objective*	*Threshold*	*Goal*	*Hardening*	*Operational*
Robustness	- Bie et al. 2016 - Carpinelli et al. 2009 - Cuadra et al. 2015 - Dunn et al. 2018 - Espinoza et al. 2016 - Ji et al. 2017 - Kwasinski 2016 - Li et al. 2017 - Liu et al. 2017 - Maliszewski and Perrings 2012 - Ouyang and Duenas 2014 - Panteli et al. 2017 - Reed et al. 2009 - Schultz and Smith 2016 - Trakas et al. 2019 - Vugrin et al. 2017 - Watson et al. 2015 - Wei et al. 2016 - Willis and Loa 2015 - Zhang and Yagan 2016	- Bie et al. 2016 - Carpinelli et al. 2009 - Cuadra et al. 2015 - Espinoza et al. 2016 - Ji et al. 2017 - Kwasinski 2016 - Li et al. 2017 - Ouyang and Duenas 2014 - Panteli et al. 2017 - Reed et al. 2009 - Schultz and Smith 2016 - Trakas et al. 2019 - Vugrin et al. 2017 - Watson et al. 2015 - Wei et al. 2016 - Zhang and Yagan 2016	- Carpinelli et al. 2009 - Cuadra et al. 2015 - Dunn et al. 2018 - Espinoza et al. 2016 - Panteli et al. 2017 - Schultz and Smith 2016 - Wei et al. 2016 - Zhang and Yagan 2016	- Panteli et al. 2017 - Schultz and Smith 2016 - Vugrin et al. 2017	- Bie et al. 2017 - DOE 2016 - EPRI 2016 - Espinoza et al. 2016 - IEA 2015 - Panteli et al. 2017 - Vugrin et al. 2017	- Bie et al. 2017 - Chattopadhyay et al. 2016 - DOE 2016 - EPRI 2016 - IEA 2015 - Li et al. 2017 - Maliszewski and Perrings 2012 - Vugrin et al. 2017
Redundancy	- Bie et al. 2017 - Cuadra et al. 2015 - Espinoza et al. 2016 - Ganin et al. 2016 - Ouyang and Duenas 2014 - Reed et al. 2009 - Trakas et al. 2019 - Wei et al. 2017 - Willis and Loa 2015	- Bie et al. 2017 - Cuadra et a. 2015 - Espinoza et al. 2016 - Ganin et al. 2016 - Ouyang and Duenas 2014 - Reed et al. 2009 - Trakas et al. 2019 - Wei et al. 2017	- Cuadra et al. 2015 - Wei et al. 2016	- Espinoza et al. 2016	- Bie et al. 2017 - DOE 2016 - EPRI 2016 - IEA 2015 - Espinoza et al. 2016 - Vugrin et al. 2017	- Bie et al. 2017 - DOE 2016 - EPRI 2016 - IEA 2015 - Vugrin et al. 2017
Resourcefulness	- Liu et al. 2017 - Panteli et al. 2017 - Vugrin et al. 2017 - Watson et al. 2015	- Li et al. 2017 - Liu et al. 2017 - Panteli et al. 2017 - Vugrin et al. 2017 - Watson et al. 2015	- Panteli et al. 2017	- Panteli et al. 2017 - Vugrin et al. 2017	- Bie et al. 2017 - DOE 2016 - EPRI 2016 - IEA 2015 - Panteli et al. 2017 - Vugrin et al. 2017	- Bie et al. 2017 - DOE 2016 - EPRI 2016 - Espinoza et al. 2016 - Esteban and Portugal-Pereira 2014 - IEA 2015 - Li et al. 2017

						- Panteli et al. 2017 - Vugrin et al. 2017
Rapidity	- Bie et al. 2016 - Cuadra et al. 2015 - DOE 2016 - Espinoza et al. 2016 - Ji et al. 2016 - Ji et al. 2017 - Kwasinski 2016 - Li et al. 2017 - Liu et al. 2017 - Maliszewski and Perrings 2012 - Ouyang and Duenas 2014 - Panteli et al. 2017 - Reed et al. 2009 - Schultz and Smith 2016 - Vugrin et al. 2017 - Watson et al. 2015 - Wei et al. 2016 - Willis and Loa 2015	- Bie et al. 2016 - Cuadra et al. 2015 - DOE 2016 - Espinoza et al. 2016 - Ji et al. 2016 - Ji et al. 2017 - Kwasinski 2016 - Li et al. 2017 - Maliszewski and Perrings 2012 - Ouyang and Duenas 2014 - Panteli et al. 2017 - Reed et al. 2009 - Schultz and Smith 2016 - Vugrin et al. 2017 - Watson et al. 2015 - Wei et al. 2016	- Ji et al. 2017 - Kwasinski 2016 - Schultz and Smith 2016 - Wei et al. 2016	- Panteli et al. 2017 - Schultz and Smith 2016 - Vugrin et al. 2017	Related to above strategies	Related to above strategies

The remainder of the section further investigates the four resilience concepts identified in Table 1: resilience principle, functional performance, performance metric, resilience strategy, and scale. This paper explores the theory behind these concepts as well as how they are applied in practice.

3.1 Resilience Principle

The 4 R's of resilience were first proposed by the Multidisciplinary Center for Earthquake Engineering Research. They include robustness, redundancy, resourcefulness, and rapidity (Bruneau et al. 2003). Although researchers have proposed many other resilience principles, the 4 R's are the most widely recognized and understood (Wilkinson 2011; Davidson et al. 2016; Kwasinski 2016; Sharifi and Yamagata 2016). Thus, when attempting to reach a broad audience that may be unfamiliar with resilience, the 4 R's offer an effective framework. In addition, as will be discuss, the 4 R's do in fact represent foundational elements of a resilient system that offer significant insight.

3.1.1 Robustness

Robustness is defined as the ability of a system or system elements to withstand a certain stress or disturbance without losing functional performance below a given threshold (Bruneau et al. 2003). Robustness emphasizes resistance or strength to short-term disturbances, such as extreme weather events that may last hours to days (Espinoza et al. 2016; Sharifi and Yamagata 2016; Panteli et al. 2017). Other terms used to describe robustness include prevention, hardening, fortification, and resistance (EPRI 2013, 2016; Li et al. 2017). A robust electric power system must maintain a specific functional performance level when a disruptive event occurs. (Cuadra et al. 2015; IEA 2015). The ability to do so is dependent on the material properties and structural dimensions of the component as well as the disturbance itself, which can vary by location, magnitude, frequency, and duration (Carpinelli et al. 2009; Dunn et al. 2018). Within the electric power system research literature, robustness is usually used to describe functional performance of individual assets, such as transmission and distribution lines, substations, and generating units.

3.1.2 Redundancy

Redundancy is the ability of elements within a system to provide the same functionality or have substitutable properties in order to maintain function (Bruneau et al. 2003; Ganin et al. 2016). Within an electric power system, redundancy is conceptualized as backup or spare capacity to meet electric service needs (Molyneaux et al. 2016). Importantly, the failure of one component in a power system will not cause the entire system to fail. Redundancy is often conceptualized as a network, where the network configuration of a transmission and distribution system is designed with path redundancy so electricity has alternate paths to flow in case of a disruption (Linkov et al. 2014; Vugrin, Castillo, and Silva-Monry 2017).

3.1.3 Resourcefulness

Resourcefulness is perhaps the least discussed of the 4 R's in relation to the energy literature. Broadly, resourcefulness is the capacity to manage operations and assets (IEA 2015). It is the level of resources available at the time of a disruption to minimize losses and restore functional performance (Sharifi and Yamagata 2016). More specifically, resourcefulness may be the capacity to identify problems as well as mobilize capital and operational assets, such as money, information, and labor, to achieve a goal (Bruneau et al. 2003). For an electric power system, that may entail having an adequate number of service crews on standby in case of a major disruption (Panteli et al. 2017; Espinoza et al. 2016) Utilities and other system operators are often responsible for resourcefulness.

3.1.4. Rapidity

Rapidity, also termed restoration, is the rate of recovery of the system or the speed at which the disruption is addressed bringing functional performance 'back' to a certain level (Reed, Kapur, and Christie 2009; Linkov et al. 2014; DOE 2016). When system losses are effectively contained, the more rapidly system operations and services can be restored. Thus, the system can return to pre-event functional performance levels (Bruneau et al. 2003; Sharifi and Yamagata 2016). It is important to note that rapidity is an outcome dependent on the other three other resilience components: robustness, redundancy, and resourcefulness. In addition, rapidity can be applied to individual assets, such as generating units, or system-wide components, such as distribution networks.

3.2 Functional Performance

Functional performance, sometimes referred to as critical functionality, is the desired service activity of each resilience component or the entire system. It is the activity or task (i.e. function) for which the system is (are) managed as established by system operators, decision-makers, or other stakeholders. This can include technical, organizational, social, and economic activities. Performance is the accomplishment of these functions (Bruneau et al. 2003; Ganin et al. 2016). Functional performance is useful for examining both the resilience of electric power systems and evaluating the effectiveness of resilience strategies. Researchers have developed a number of quantitative resilience models that apply functional performance to electric power systems. These include statistical, computational intelligence, and mathematical programming methods. Some of these methods take a more general approach, whereby the entire system is modeled as a single entity. Other methods are structural-based, taking into account specific system elements. There is also a differentiation between static and dynamic models, with the latter incorporating time-dependencies (Hosseini, Barker, and Ramirez-Marquez 2016; Debnath and Mourshed 2018). Functional performance models can include environmental, infrastructure, electric service, and customer behavior variables (Ji, Wei, and Poor 2017). Examples include fragility curves that measure the robustness of electric utility poles to windstorms or a network graph that examines the centrality of nodes, such as substations, to the rest of the electric power system during a hurricane (Hosseini, Barker, and Ramirez-Marquez 2016; Bie, Lin, and Li 2017; Dunn et al. 2018; Trakas et al. 2019). The framework in this paper defines functional performance of electric power systems according to four model components: metric, objective, threshold, and goal.

3.2.1 Functional Performance Metric

Metrics quantify functional performance and other model parameters. They define the unit of measurement, usually at the ratio or interval level, allowing for the performance of specific resilience principles – robustness, redundancy, resourcefulness, or rapidity –to be measured as a continuum in space and time (Bie, Lin, and Li 2017; Ji, Wei, and Poor 2017). Functional performance metrics provide a standard of measurement and the basis for a common understanding. Metrics quantify electric power generation, distribution/transmission, and consumption. On the generation side, functional performance metrics include Expected Energy Not Supplied (EENS) as an absolute value in megawatt-hours over a given period and percent of generation capacity online (Espinoza et al. 2016; Panteli et al. 2017). For distribution and/or transmission, the number of faults per 1000 km length of overhead lines and percent of transmission lines online are often used (Panteli et al. 2017; Dunn et al. 2018). On the consumer or load side, metrics include the percentage of customers or critical facilities with power, customer-days without power, and Value of Lost Load (VOLL) as the interruption cost of service in dollars per event (Ouyang and Deunas-Osorio 2014; DOE 2016; Vugrin, Castillo, and Silva-Monry 2017). System-wide functional performance metrics are also cited in the research and industry literature. These include the average duration of unscheduled outages and time to restoration (Maliszewski and Perrings 2012; Bie, Lin, and Li 2017).

It is important to note that industry standard reliability metrics, such as the system average interruption duration index (SAIDI), are often used as resilience performance metrics because of their simplicity. Some argue that reliability metrics are not appropriate proxies because reliability metrics are not inherently defined according to a specific disruption. Whereas resilience should examine the system performance before, during, and after the disruptive event, reliability metrics focus on post-event performance (Ji, Wei, and Poor 2017; Li et al. 2017). Nonetheless, standard reliability metrics are commonly used and cited as performance metrics for electric power system resilience both in the research literature and electric power industry trade literature (Espinoza et al. 2016; DOE 2016; Willis and Loa 2015).

3.2.2 Functional Performance Objective

For use in planning and management activities, functional performance should have an associated objective function, whereby there is a desire to maximize to, maintain at, or minimize from a given level of performance (Keeney 1992; Schultz and Smith 2016). For electric power systems, functional performance objectives most often include maintaining a certain level of electric service to customers or the structural integrity of an infrastructure asset (EPRI 2013). Functional performance of the system changes as the disruption progresses through time (Hosseini, Barker, and Ramirez-Marquez 2016; Li et al. 2017). A degradation in functional performance is associated with an overall decrease in resilience. While the notion of a functional performance objective is often included in resilience studies, it is rarely addressed in an explicit manner. Thus, it useful to understand how functional performance objectives are applied to analytical models that examine resilience.

Many energy resilience studies apply a single functional performance objective to the entire power system, such as minimizing service interruption costs, regardless of a specific disturbance (DOE 2016). This is termed general resilience. It entails evaluating the functional performance of a system with respect to a wide range of known and unknown disturbances (Folke et al. 2010; B. Walker and Salt 2012). Studies that take this approach use simplified and idealized models to measure resilience (Ganin et al. 2016; Zhang and Yagan 2016; Li et al. 2017). Thus, functional performance for general resilience is sometimes based on a limited view of electric grid performance in order to reduce model complicatedness (Kwasinski 2016). Limiting customer outage duration is an example of such a functional performance objective. A general resilience approach may be inadequate for short-term planning and management activities if the range of complexity and dynamic behavior of the real-world system is not captured. Nonetheless, this is often the most practical resilience planning approach, where it is not feasible to model a wide range of technical, economic, and environmental variables using as a single resilience measure.

Alternatively, a bottom-up approach establishes functional performance objectives for multiple system components and services. Functional performance is measured in relation to known disturbances and controlling variables are identified. This approach is known as specified resilience (Folke et al. 2010; B. Walker and Salt 2012). A specified resilience approach is particularly useful for power systems planning at the tactical and operational levels since the functional performance of system components can be optimized for local disturbances across the electric grid (van der Merwe, Biggs, and Preiser 2018). A specified approach can include setting functional performance objectives for the structural integrity of distribution poles to a certain magnitude earthquake or the power quality of electricity on the grid during a heatwave (Li et al. 2017). Thus, each system component is assessed in regard to a specific threat. This type of characterization is advantageous in the decision-making process since system operators and other stakeholders, including customers, will often have competing interests and, therefore, different management objectives (Thekdi and Santos 2018). No single objective is likely sufficient for planning and managing an electric power system since, in all likelihood, the resilience of one component of the system is dependent on the resilience of another component.

3.2.3 Functional Performance Threshold

Once appropriate metrics and objectives are defined, practitioners can then examine the impact of the disruptive event on the resilience of the electric power system by using thresholds (Kwasinski 2016; Wei et al. 2016). Functional Performance – in relation to natural hazards – is marked by abrupt changes, as opposed to the minor fluctuations seen under normal operating conditions (Bruneau et al. 2003). These abrupt changes to system performance can cause the entire system or system elements to reach a threshold or tipping point. Above or below this specific value, as quantified by the metric, functional performance is no longer satisfactory (B. Walker and Salt 2012; Schultz and Smith 2016). Functional performance thresholds, therefore, quantify critical points at which disruptions may trigger a degradation or collapse of the system below a satisfactory level of functional performance. Thresholds establish minimum or maximum values for each objective (Molyneaux et al. 2016).

If a threshold is crossed, then change occurs causing a critical transition. The system can return to equilibrium or organize along a different trajectory (Folke et al. 2010; Sharifi and Yamagata 2016). At any point beyond the threshold, the system or system elements begin to experience adverse impacts and performance is affected. For example, Seattle City Light found overhead power lines can sustain winds up 40 mph. Above this wind speed threshold, overhead power lines begin to fail, thereby reducing the functional performance of the electric power grid (DOE 2016). If the damaged overhead lines are not quickly repaired and system degradation continues, then the electric grid cannot return to an equilibrium state of functional performance.

Thresholds, however, can be difficult to establish for large systems, as component complexity and uncertainty increases (DOE 2016). To accurately establish thresholds, one needs to know how each system element and/or the entire system reacts to a wide range of disturbances at varying magnitudes. Thresholds can also change. If system operators learn from previous disturbances, they then have a better chance to successfully respond to future disturbances by implementing resilience strategies (B. Walker and Salt 2012). These adaptations should positively increase or decrease functional performance thresholds so that the system can absorb a larger disturbance.

3.2.4 Functional Performance Goal

A functional performance goal is the preferred level of functional performance for the objective. Whereas as a threshold is the minimum level of performance, a goal is the ideal level of performance possible to achieve (Keeney 1992). For example, if the objective is to minimize substation damage during a storm then a corresponding goal may be to have 90% of transformers located within the substation operational. A goal is either achieved or not. If it is achieved, we can conclude that the system or system element is functioning at a high level of performance. Any functional performance level between the goal and threshold should be considered satisfactory. Goals are also referred to as targets and states, especially in the quantitative modelling literature (Espinoza et al. 2016; Panteli et al. 2017). In some cases, the term status quo is used to describe a functional performance goal (Schultz and Smith 2016).

Goals can help achieve objectives in the near-term by establishing measurable performance targets. Goals can also increase functional performance levels in the long-term by providing comparative performance standards. Such performance targets and standards motivate stakeholders by clearly defining expectations (Keeney 1992; Ji et al. 2016). Just as thresholds change, so do goals. As systems become more resilient to certain disturbances, system operators can set new goals that reflect a higher level of desired functional performance. Instead of 90% of transformers being operational at a given substation during a storm, a new goal might be to have 95% of transformers operational. It must be noted that this study defines goal according to the decision-science literature. Thus, a goal characterizes an objective function and has a defined unit of measurement (Keeney 1992).

3.3 Resilience Strategy

A resilience strategy is an action, regulation, or policy that increases functional performance, thus, the system's overall resilience during a disruption. System managers seek to prevent or minimize undesired consequences (Hosseini, Barker, and Ramirez-Marquez 2016). This is accomplished by building system capacity to resist, absorb, and recover from the adverse events (B. Walker and Salt 2012). Strategies to maintain or increase the resilience of a system are divided into two categories: hardening and operational. Hardening strategies focus on the physical infrastructure of the electric power system, while operational strategies focus on the activities that keep the system running on a daily basis. Both approaches mitigate vulnerabilities in the electric power system to promote physical, economic, ecological, and social resilience. It is important to note that resilience strategies are sometimes referred to as resilience solutions or measures within the research and industry literatures (DOE 2016; EPRI 2016; IEA 2015).

Hardening strategies make physical changes to the electric power system (Dunn et al. 2018). A study conducted by Espinoza et al. (2016) found that for windstorms and floods, it is most effective to improve the robustness of the transmission infrastructure in order to increase overall system resilience. In a similar study, Panteli et al. (2017b) tests three types of resilience improvement approaches for the United Kingdom transmissions system. The approaches focused on redundancy, robustness, and responsiveness. They found that robustness strategies have the highest impact on increasing resilience of the electric transmission system when faced with severe windstorms. Some common hardening strategies are to upgrade wood utility poles to more robust materials, like steel or concrete; place distributions lines underground; elevate substations; employ hydrophobic coatings on transmission system components; and build floodwalls around key assets. (Bie, Lin, and Li 2017; DOE 2016).

Operational strategies aim to improve the overall system efficiency in case of disruptions through a combination of siting and design, system monitoring, data collection, and personnel training (Li et al. 2017). Proper siting and design are the first operational strategy that practitioners can undertake. Initially locating infrastructure assets in places less vulnerable to certain natural hazards, such as windstorms, is far less expensive in the early planning process then relocating and/or retrofitting assets once they are in place (Chattopadhyay et al. 2016). System monitoring and data collection technologies are also increasingly important operational tools as distributed energy resources are deployed across the grid. The development of advanced outage management systems provides operators with real-time network information, thereby allowing dispatchers to prioritize response efforts. More innovative strategies include airborne damage assessment through the use of drones (EPRI 2013). These strategies allow for better grid visualization, customer communication, and reporting (Esteban and Portugal-Pereira 2014). Training personnel who operate and service the electric power system is another type of operational strategy. Personnel can be trained for emergency response and repair as well as hazard modelling and forecasting (IEA 2015). Operational strategies also include vegetation management (e.g. tree trimming) around transmission and distribution components. One study found that interactions between overhead power lines and vegetation had a more significant impact on the duration of power outages than infrastructure type (Maliszewski and Perrings 2012).

Generally, hardening strategies are more costly than operational strategies, involving capital and labor-intensive projects. For example, upgrading wood utility poles costs between 16,000 to 40,000 USD per mile. Placing distribution lines underground costs between 100,000 to 5,000,000 USD per mile while the cost for burying transmission lines is between 500,000 to 30,000,000 USD per mile. In contrast, the cost of vegetation management is only 12,000 USD per mile (DOE 2016). Importantly, these strategies are only effective relative to certain events. For example, while placing power lines underground may make them more robust to windstorms, undergrounding lines can increase the vulnerability to earthquakes. In reality, a combination of hardening and operational strategies is usually deployed. Microgrids, for example, harden the grid by adding redundant generation capacity to the system but also aid the grid's overall operation by providing blackstart capabilities and limiting cascading failures. Such strategies require long-term planning processes that can assess the costs and benefits of different resilience strategies.

3.4 Scale of action

The scale of action is the spatiotemporal extent and resolution at which practitioners choose to focus their planning and management activities (Calvert, Pearce, and Mabee 2013). As with most complex systems, electric power systems can operate at multiple spatial and temporal scales. Regarding the spatial dimension, power grids span city, county, regional, and national boundaries (IRENA 2015; Tozzi Jr. and Jo 2017). In addition, energy technologies are implemented at different material sizes, from rooftop solar panels to offshore wind farms. In terms of the temporal dimension, electricity demand changes on an hourly, daily, and seasonal basis. System operators must accurately forecast load fluctuations for frequency and voltage control. Generation is also variable over time, with renewable resources, such as solar energy, fluctuating frequently due to cloud cover and daily and seasonal solar position.

Due to these characteristics and the evolving inclusion of more diverse sets of technologies and functionalities, electric power systems have become hyper-sizable. They can operate at a range of technical, social, economic, and geographic scales. As a result, resilience will also operate on multiple scales as the size, configuration, and function of the power system changes (G. Walker and Cass 2007; Ji, Wei, and Poor 2017). Understanding the scale of action can help determine appropriate functional performance objectives, performance metrics, and strategies for resilience planning. Therefore, the resilience measurement framework presented in Table 1 takes a multiscale approach. We believe that when examining the resilience of an electric power system, a three-scale micro-meso-macro classification scheme is most appropriate. This organizes the power system from a low to high level of spatial aggregation, where individual assets are connected to the wider socio-technical energy system (G. Walker and Cass 2007; de Boer and Zuidema 2015).

The micro or asset-level is associated with the lowest aggregation levels and focuses on the function of specific infrastructure elements. Electric power system infrastructure can include utility poles, distribution lines, inverters, and generation units. Analysis, monitoring, and management at this scale focuses on the performance of specific assets. High-resolution data at this level, however, can be difficult to obtain. Utilities might not have monitoring on all circuits or even substations (IRENA 2015). Furthermore, this scale contains limited information on the interactions of elements.

The meso or service area-level makes a connection between infrastructure elements and end-users (i.e. electricity customers) in specific geographic areas. This provides information about the locational value and services of energy resources. Locational value is defined as "the local generation capacity needs, avoided or increased investments in distribution infrastructure, safety benefits, reliability benefits, and any other savings the distributed resources provides to the electric grid or costs to ratepayers of the electrical corporation" (deLlano-Paz, Calvo-Silvosa, and Soares 2017: 27). At the service-area scale, dynamic consumer behavior is examined by analyzing load curves, outages, and technology adoption. Variables external to the power system, like land cover, are also included. A service-area scale provides a more heterogeneous view of the electric power system by including both assets and actor interactions. The service area scale is of particular importance when examining socio-economic differences among users.

The macro or system-level is the highest aggregation level, in which the overall functioning of the system is described. At this scale, system assets and service areas are aggregated to understand how the entire electric power systems operates as a network formed by nodes (i.e. substations) and links (transmission lines). Because of this top-down approach, it is more feasible to examine rate economics, such as cost-based incentives for customers, and forecast transmission and distribution capacities. Although one gains a better understanding of system-wide operations at the macro scale, heterogeneity is lost as power system assets and service areas are aggregated.

It is important to note that the scale of action is always specific to the decision situation. Certain constraints, such as data availability and institutional practices, influence which scale is most appropriate. However, a micro-meso-macro approach highlights the range of resilience objectives, metrics, and strategies available for electric power system planning and design.

4. Discussion

The ability to measure electric power system resilience and integrate that information into planning and management activities is critical as energy systems confront a range of natural and man-made threats. Without first assessing associations and differences among relevant concepts, resilience is limited in its practical application and the development of standardized practices is hindered (Davidson et al. 2016). The framework presented in this paper – Table 1 – helps inform more specialized analytical models by examining different modes of treatment for measuring electric power system resilience at multiple spatial scales. The resilience measurement framework examines four fundamental concepts: resilience principle, functional performance, resilience strategy, and scale of action. This study has five primary findings.

First, this study finds that although the 4R's – robustness, redundancy, resourcefulness, and rapidity – are well represented in the literature, resilience studies generally focus on quantifying robustness and rapidity. This may be because techniques for measuring these concepts largely draw from the structural engineering discipline, where analytical methodologies are well established. Furthermore, the unit of measure for rapidity – time – is fixed, making computation much simpler. In contrast, redundancy and resourcefulness vary far more in dimensions for measurement. Both redundancy and resourcefulness draw from multiple disciplines, including engineering, network science, graph theory, economics, and business management. Such a diverse range of perspectives make any attempt to standardize definitions and, by extension, measurement techniques more challenging.

Second, this paper finds that functional performance objectives are rarely defined in terms of targeted and measurable objectives. There is often a conflation between functional performance objectives and functional performance metrics. Objectives define the expected functional performance of the asset, service area, or system while metrics define the unit of measurement. Only a few studies explicitly differentiate them (Watson et al. 2015; Kwasinski 2016; Schultz and Smith 2016; Panteli, Mancarella, and Trakas 2017; Vugrin, Castillo, and Silva-Monry 2017) Functional performance objectives, such as 'electric power delivery' or 'service restoration', must be further refined to include a specific management objective that can be measured. Instead of 'electric power delivery', a more appropriate functional performance objective is: maintain electric power service to X percent of households in the utility's service area. This new functional performance objective is 1) targeted towards utility customers and 2) includes a defined measurement component from which a performance metric can be derived. If we are to transition from resilience thinking to resilience planning and management, it is imperative to specify functional performance for all elements of the system. Poorly defined and bounded functional performance objectives only serve to increase confusion about resilience. This results in multiple interpretations of the same concepts, thereby relegating resilience performance to abstract terms with limited practical application (Keeney 1992; Davidson et al. 2016).

Third, functional performance models involve tradeoffs between precision, resolution, accuracy, and efficiency. Models that measure system-wide resilience tend to include numerous variables, relationships, and processes in order to capture the heterogeneity of the system. For example, one study examines the resilience of power distributions systems to severe weathering using dynamic failure-recovery processes and customer impact models (Wei et al. 2016). Practitioners may find such performance models complicated and, therefore, difficult to understand or incorporate in their decision-making framework. However, many of the social, economic, and technical structures and processes found in real-world electric power systems are indeed complex and context-dependent. Therefore, they are not easily generalized or simplified. Developing a simplified performance model may lead to an incomplete or inaccurate understanding of the system under study, thereby sacrificing precision and resolution (Janssen and Ostrom 2006, Almaraz 2014).

Fourth, this study find that functional performance thresholds and goals are rarely established. As discussed in the previous section, functional performance thresholds are critical points at which disruptions may trigger a degradation or collapse of the system. Goals are the ideal state of functional performance. If thresholds and goals are not established, then it becomes difficult to accurately assess and forecast resilience. Practitioners will find it difficult to answer such questions as, what fraction of households need to have electric service during a windstorm before the resilience of the electric power system is degraded beyond an acceptable level? To answer this question, both a threshold and goal value for the functional performance objective need to be established. Taken together, a threshold and goal provide a range of functional performance values that satisfy a management objective. Once established, they enable practitioners to assess the state and magnitude of resilience.

Fifth and last, the majority of electric power system resilience studies do not address scale. Currently, most research examines the electric power system from either a high-level, abstract perspective with little attention paid to the actual configuration of the system in time and space or a detailed, operational perspective with no regard for the broader geographic landscape. Thus, there is a critical research gap within energy resilience. Research needs to bridge and connect high level geographic concepts with the detail-oriented infrastructure and operational planning considerations. This will provide a middle-ground where regional decision-makers and system operators can address power system problems and concerns that span jurisdictional boundaries.

The measurement framework – Table 1 – provides an instrument to compare resilience measures and link those measures to actionable strategies at asset, service area, and system scales. Practitioners can use this framework to develop more specialized analytical models to assess the resilience of electric power systems to specific threats, such as windstorms or floods (Tozzi Jr. and Jo 2017). The incorporation of the framework in planning and management activities is particularly applicable to stakeholder-informed and driven processes given its multidimensional and multi-scalar design. Regardless of the specific decision situation, all stakeholders should share a common understanding of resilience principles, functional performance models, and strategies. The resilience measurement framework presented in Tables 1 and 2 facilitates decision-making by identifying concepts important to electric power system resilience. The aim is to transition high-level resilience concepts from theory to practice (B. Walker and Salt 2012; Sellberg et al. 2018).

5. Conclusion

Currently, the electric power systems and, more broadly, energy systems research literature lacks instruments for symmetrically comparing resilience concepts. Therefore, this study develops a measurement framework that compares measurement techniques at different spatial scales. It assesses four fundamental resilience concepts – resilience principle, functional performance, resilience strategy, and scale of action – as well as provides examples of how these concepts are used in practice. The framework is intended to inform more specialized analytical resilience models that examine specific threats to electric power systems. For use in an applied context, functional performance must be defined as a targeted and measurable objective that includes appropriate metrics, thresholds, and goals. In addition, scale is rarely addressed although power grids span geographic regions and must operate at varying temporal resolutions.

Future research should focus on valuing resilience, especially at the utility scale. Utilities will likely need an econmic incentive to deploy resilience strategies (Bond et al. 2017; Shang 2017; Laws et al. 2018) . Empirical research is also needed to examine the impact of specific resilience strategies, such as battery storage or digital technologies. It is still unknown how resilient most electric power systems actually are prior to a disaster occurring. Furthermore, evaluation of resilience strategies is under-represented within resilience research for electrical power systems largely due to the need for targeted and measurable objectives across the 4 R's (Esteban and Portugal-Pereira 2014; Panteli et al. 2017).

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Chapter Three

Spatiotemporal Patterns of Electric Power System Performance:

A Case Study about the Resilience of Puget Sound Energy

1. Introduction

Infrastructure, including electric power systems, is frequently exposed to both natural and man-made hazards. We generally expect these infrastructure systems to withstand and recover from hazards of a certain magnitude in order to maintain functional performance over time. This is termed resilience. More specifically, a resilient system is one that can absorb, adapt, and recover from disruptions by hazards (often called stressors) while still maintaining a specific function (Walker and Salt 2012). Electric power systems offer a unique case study for the examination of infrastructure resilience because they 1) incorporate different infrastructure types, 2) provide critical services, and 3) have social and economic importance to the surrounding community.

Currently, most researchers examine the resilience of electric power systems from either a regional perspective that treats space as a homogenous landscape (Espinoza et al. 2016) or operational perspective that treats space as an abstracted network diagram (Bie, Lin, and Li 2017). While these traditional research approaches have undoubtedly advanced our understanding of electric power systems, the foundational concepts of geography – space, place, scale, and time – in relation to broader socioeconomic and political patterns are often overlooked. Thus, there is a critical research gap within electric power system resilience (Truffer, Murphy, and Raven 2015; Kowalski 2019).

To fully examine the relationship between electric power systems, geography, and resilience, researchers and practitioners should address two issues. First, integrated space-time research techniques are needed. Both the spatial extent and temporal duration of the disruption are key components to understanding resilience (Stoeglehner, Niemetz, and Kettl 2011). Without understanding spatiotemporal dimensions, it is difficult to capture the dynamic nature of certain phenomena, such as the response of an electric grid to severe storm (Yu and Shaw 2011). Since complex systems operate at multiple spatiotemporal scales, researchers must understand the relationship between scales (Walker and Salt 2012: 195). Therefore, it is important to explore new descriptive and analytical tools and methods for integrating spatiotemporal data analysis.

Second, it is critical to assess the functional performance of the system in question before actually measuring resilience. Functional performance is the desired service activity of the system. It is the function (i.e. activity or task) for which the system is managed as established by system operators, decision-makers, or other stakeholders. This can include technical, organizational, social, and economic activities. Performance is the accomplishment of these functions. Examples of functional performance include maintaining the structural integrity of infrastructure assets and reducing outage times (Bruneau et al. 2003; Ganin et al. 2016). Functional performance is a necessary precondition of resilience since it helps establish specific metrics, goals, and thresholds (Keeney 1992). An accurate performance assessment, therefore, must first be established before the resilience of specific system components is analyzed.

As an initial step towards comprehensively understanding the resilience of electric power system, this study directly addresses these two issues by presenting a geographic approach to performance assessment. The study evaluates the functional performance of the Puget Sound Energy (PSE) electric power grid in King County, WA to unplanned outages due to storms from

2013 to 2017 using spatiotemporal models. It specifically focuses on the performance of the PSE system at different spatiotemporal scales. The purpose is to 1) understand spatiotemporal patterns of electric power system performance and 2) gain a better understanding of how geographic information system (GIS) practices are used for space-time resilience approaches.

This paper will benefit the multiple local, state, and federal government agencies as well as other public stakeholders responsible for electric power system management. The findings may be particularly useful to electric utilities, utility customers, regulatory commissions, and other practitioners. The following section describes the project methods, including the analytical procedures used to measure and analyze system performance. Next, the results of the project are discussed using maps and graphs to visually represent electric power system performance in King County, WA. Finally, this report concludes by discussing some generalizations gathered from the study and future recommendations for further research into electric power system resilience from a space-time perspective.

2. Methods

The planning and management of complex systems benefits from a well-formed decision-making approach (Nyerges et al. 2014). This study develops a spatiotemporal functional performance assessment of the Puget Sound Energy electric power system in King County, WA. The performance assessment describes the PSE electric power system and identifies the performance of critical system functions, including the delivery of electric power to customers. The goal is to understand the system in which the critical infrastructure components operate and how well the system operates under stress. The performance assessment is developed using quantitative geospatial and statistical analytic methods. Electric power system outage data are obtained from Puget Sound Energy. The following subsections will discuss in more detail the PSE electric power system data as well as descriptive and analytic methods used to construct the performance assessment model.

2.1 Study Area and Electric Power Outage Data

Electric power system outage data were obtained directly from PSE. The dataset covers all PSE electric utility services areas within King County, WA from January 1, 2013 to December 31, 2017. Not all cities and townships within King County are served by PSE. Those unserved areas, such as the City of Seattle, are therefore excluded from analysis. In total, PSE provides electric utility service to 30 cities and townships, including unincorporated areas, within King County. The outage data spans five years, from 2013 to 2017. January 1, 2013 was chosen as the start date because that is when PSE implemented an automated data outage management system. The end date – December 31, 2017 – is the last year for complete data at the time of this study. This five-year period, therefore, represents the most recent, complete, and accurate outage data for PSE service areas in King Country. Figure 1 shows the location of substations operated by PSE and the King County boundary that is served by PSE. Note that two substations in southern King County fall outside of the county boundaries. Those substations are, however, served by transmission and distribution lines in King County and, therefore, are included in this study.

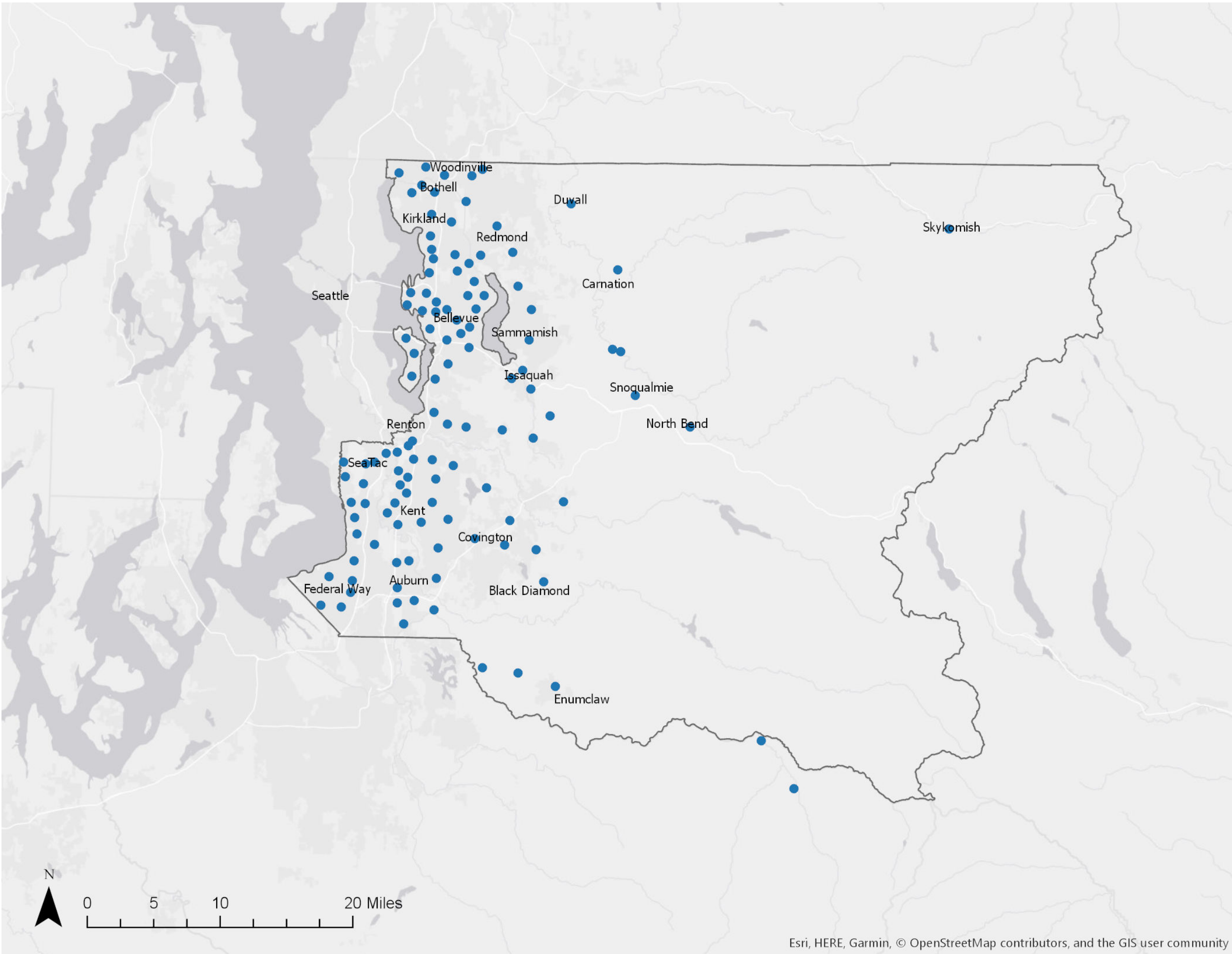

Figure 1: PSE Substations and outline of PSE service territory in King County, WA.

Outage data are recorded at the circuit level. Each data record represents a single circuit outage on the PSE distribution grid. Outages are recorded on a per day basis and have a temporal resolution of hours, minutes, and seconds. The outage database obtained from PSE contains attribute data for each outage event as well. This includes outage start date and time, duration, number of customers impacted, customer outage duration, reference circuit description, outage cause, equipment type involved in the outage, and storm category. Importantly, outage data includes both planned and unplanned outages. Over the five year period there were 30,416 planned and unplanned outage events recorded for PSE service areas in King County, WA.

For confidentiality reasons, the geographic locations of the circuits where the outages occurred are not provided by PSE. Instead, each outage event has an associated reference circuit description that contains a facility code for the substation that serves the circuit. Thus, outages are aggregated to the substation level (Figure 1). Substations, therefore, serve as the most detailed level of analysis for this study. To prepare the data for analysis, each outage record was first associated with its corresponding substation. As of 2017, PSE operates 118 substations in King County. Substation street addresses were geocoded in ArcGIS Pro using an address locator based on the King County, WA road network as the reference dataset. This provides the latitude and longitude of each PSE substation in King County, WA and, by extension, the geographic location of each aggregated outage record. Next, outages caused by storms were selected from the dataset using the storm category attribute. From 2013 to 2017, there were 5,335 storm-related outages in PSE service areas within King County. Storm outages are then categorized by meteorological season: Spring, Summer, Autumn, or Winter.

2.2 Performance evaluation

To analyze the behavior of the PSE electric power system in space and time, this study uses ESRI ArcGIS Pro and Tableau software to conduct spatiotemporal pattern analysis. Prior to conducting the pattern analysis, descriptive statistics are calculated for each element. Graphs are also produced showing the distribution of electric outages. This helps to identify outliers in the dataset and indicate what patterns we might expect when conducting the pattern analysis.

Global and local pattern analyses are conducted for the micro spatial scale elements. Global pattern analysis examines the geographic pattern of features (i.e. points, lines, or polygons) in an area. This study uses Global Moran's I to analyze the degree to which features are clustered together or exhibit spatial autocorrelation, taking into consideration attribute values and feature locations when examining clustering. In this case, the features under consideration are substation locations. The attribute values used to weight each feature is the functional performance of the PSE electric power system, operationalized as customer outage minutes. This is discussed in further detail in the following section.

Importantly, Moran's I examines clustering of all similar values. It returns index scores indicating the degree to which the features are clustered as well as z-scores that indicate the probability that the observed clustering differs from the expected random clustering. Since the index is relative to the data values, z-scores show the statistical significance of clustering. Features with high positive z-scores indicate that they are surrounded by similar values, while features with low negative z-scores indicate they are surrounded by dissimilar values. Since Global Moran's I analysis did indicate that statistically significant clustering is present, this study then uses local pattern analysis to examine precisely where customer outage minutes are clustered in the PSE King County service territory.

Unlike global pattern analysis, local pattern analysis performs a calculation for every observation or feature, showing where clustering is spatially occurring. This study used Getis-Ord Gi* to examine clustering. The value of each feature in the study is included in the analysis. Thus, when performing Getis-Ord Gi* analysis a single feature with a very high value will show up as a hot spot even if neighboring values are low.

All pattern analyses use Euclidean (straight-line) distance as the distance measure and fixed distance bands as the conceptualization of spatial relationships. Fixed distance bands are appropriate for this study because the units of analysis – substations (points) – vary in distance to each other and do not have contiguous neighbors. A fixed distance band of 5 miles is selected for substations as this allows for each feature to have multiple neighbors. There are four substations located in sparsely populated areas of King County that did not have neighbors based on the chosen fixed distance band to associate with clustering. Because these substations are relatively isolated, they are excluded from local pattern analysis.

After conducting the spatial pattern analysis described above, this study then uses the newly released ESRI Space Time Cube (STC) to analyze functional performance of the PSE electric power system through an integrated spatiotemporal framework. This helps examine patterns in substation functional performance that might otherwise be obscured when analyzing data in two dimensions. Unlike traditional spatial pattern analysis, as just discussed, the STC treats time as a fundamental property of the phenomenon under study rather than just an attribute. The STC has other analytical advantages. As part of the Space Time Pattern Mining toolbox, the STC also provides interactive analysis and visualization, whereby the user can dynamically zoom and pan to specific geographic locations and temporal segments in 3-dimensions

As seen in Figures 2 and 3, timestamped spatial data features (points or polygons) are structured into “A netCDF data cube by generating space-time bins with either aggregated incident points or defined features associated with spatiotemporal attributes” (ESRI 2019). The result is a three-dimensional cube populated with rows, columns, time steps, and attributed data. Each bin, therefore, represents a specific instance of the measured phenomenon in space and time (Figure 4).

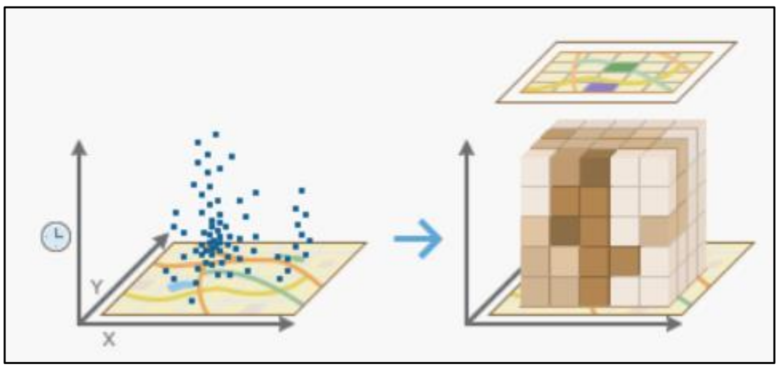

Figure 2: STC by aggregating points (ESRI 2019)

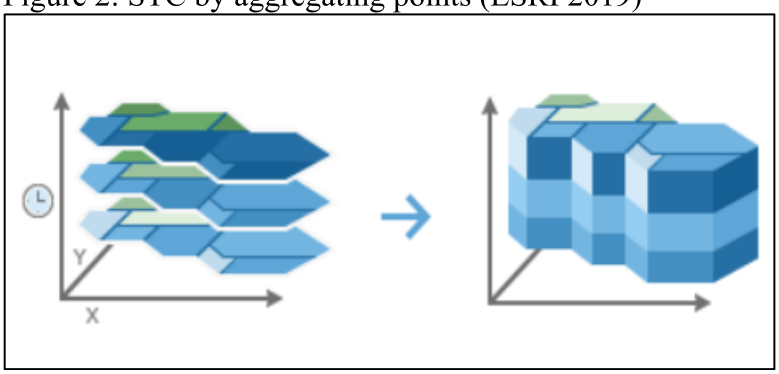

Figure 3: STC by defined locations (ESRI 2019

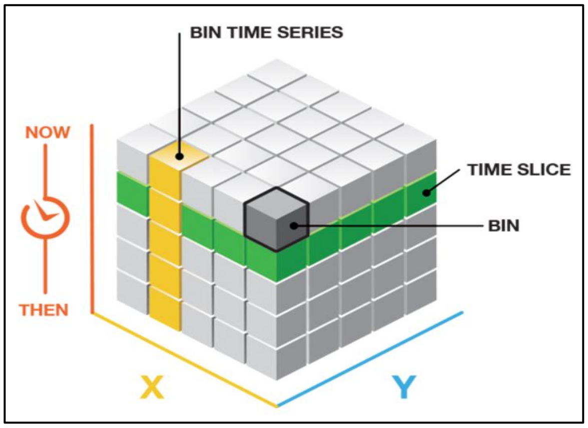

Figure 4: Space-time Cube (ESRI 2019)

The STC is created by defined outage locations at the substation spatial scales. The temporal structure of the cube is defined according to a one month time-step interval, with the start time of the STC aligned to 01/01/2013. Daily outages are aggregated together on a monthly basis from 01/01/2013 to 12/31/2017. For each time-step (i.e. month), the attributes within each bin are summarized by adding the total attribute value for each bin. The attributes are customer outage minutes. Empty bins – locations or time-steps where there is no data – are filled with a value of zero indicating that there are no outages.

After creating the STC, an Emerging Hot Spot Analysis is then performed. This tool is similar to the Getis-Ord Gi* local pattern analysis. The key difference is that the tool analyzes the clustering of values not only in space but also in time. Each bin has spatial as well as temporal neighbors that are analyzed within the context of neighboring bins as seen in Figure 5. The advantage of the STC is its ability to analyze integrated spatiotemporal data and view that data in 3D.

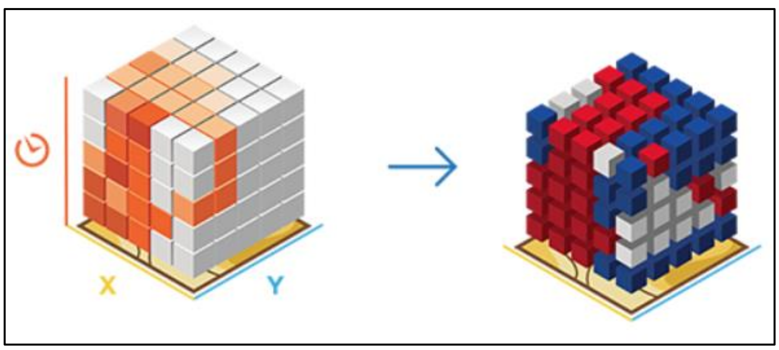

Figure 5: STC Emerging Hot Spot Analysis (ESRI 2019)

Since the PSE dataset provides information on customers' outages only and no other types of system functionality, this study defines functional performance for the resilience of the PSE electric power system as the maintenance of customer electric power service during weather-related disruptions. The dataset provides four metrics for customer electric power service. They include the number of outages, outage duration, number of customers affected per outage, and customer outage minutes per outage. Of those four metrics, customer outage minutes

(COMs) best captures the functional performance of the PSE electric grid since it takes into account the extent (i.e. number of customers affected) and duration of outages (Vugrin, Castillo, and Silva-Monry 2017). COMs are calculated by multiplying the number of affected customers by the duration of the outage.

There are three important issues to note. First, if we go back to the definition of functional performance, we can see that COMs do not really represent the desired service activity of the system. System operators certainly do not want their customers to experience outages. Rather COMs are the inverse measure of minutes of customer service, the true task of the system (i.e. to provide customers with electric service). The dataset, however, does not provide data on the number of customers in the service territory. Therefore, COMs, a measure of performance degradation, is used as the best proxy of functional performance. Second, it is also important to distinguish resilience from reliability. Resilience is how the functional performance of a system responds to low-probability, high-consequence disruptions, such as severe weather events. Reliability, in contrast, is how the functional performance of system responds to high-probability, low-consequence disruptions encountered during normal operating conditions, such as equipment failures (Vugrin, Castillo, and Silva-Monry 2017). To address this issue, this study includes outage events only that result from storm events. Lastly, it is possible that high COM values are simply associated with areas that have more customers. To exclude such a relationship, this paper conducted an exploratory linear regression analysis whereby substation COMs were modeled against zip code population (as a proxy for the PSE customer base served by each substation). No significant association was found.

3. Results

The results of this study are presented in the following subsections. First, the descriptive statistics of PSE outages are analyzed to describe and examine the temporal distribution and magnitude of outage events from 2013 to 2017. Next, functional performance is evaluated. Pattern analyses are used to identify spatial autocorrelation among substation features and customer outage minutes. Local pattern analyses are conducted to identify where the clustering of high/low value customer outage minutes is occurring. The results of both the spatial pattern analyses and STC pattern analysis are presented.

3.1 System Description

From 2013 to 2017, there were 5,335 outage events within the PSE service territory in King County, WA. As evidenced by Figure 6, customer outage minutes (COMs) for the PSE service territory in King County vary annually. COMs peak in 2014 with 227,733,517 minutes and are lowest in 2013 with 53,875,947 minutes. Individual outage events have a mean COMs of 114,204.93. When examining outages on a daily basis in Table 3 and Figure 7, we see that the largest outage day occurred on October 25, 2014. This resulted in 83,981,327 COMs. The mean daily COMs is 7,712,446.90. Outages do not occur on the vast majority of days. Of the 1,826 days during the study period, outages occurred on 79 days or 4.3% of days only. When examining Figure 7, it is also evident that outages cluster together in time. They are not evenly distributed throughout the year. Although this is expected, the periods when electric service is fully maintained is also important and warrants further analysis.

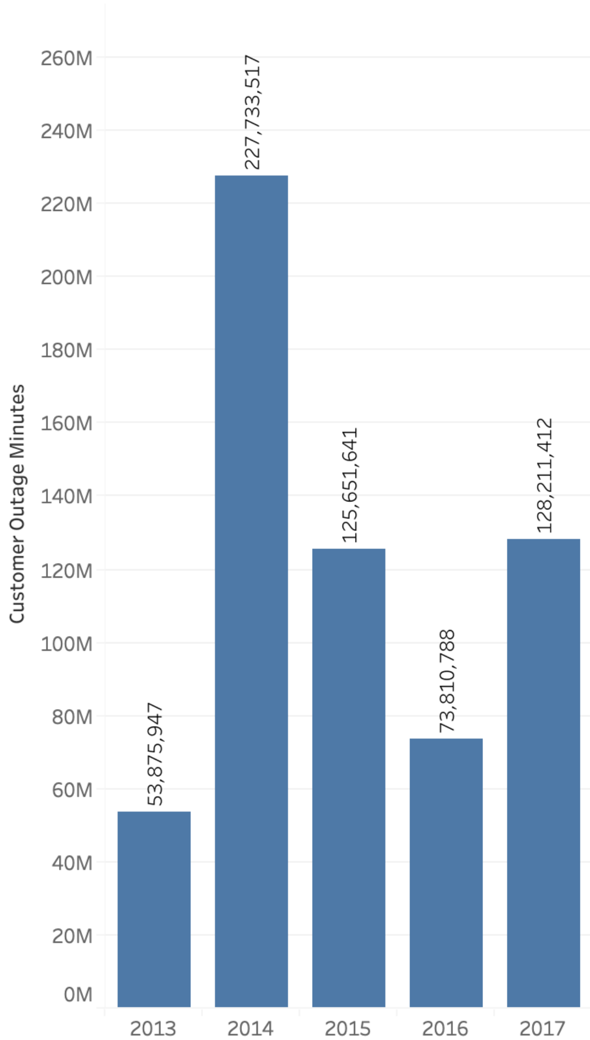

Figure 6: Customer Outage Minutes by Year

	Mean	N	Std. Deviation	Sum	Minimum	Maximum
Customer Outage Minutes	114,204.93	5,335	367,069.35	609,283,305	6	7,9671,66

Table 2: Descriptive Statistics for Customer Outage Minutes by Outage Event

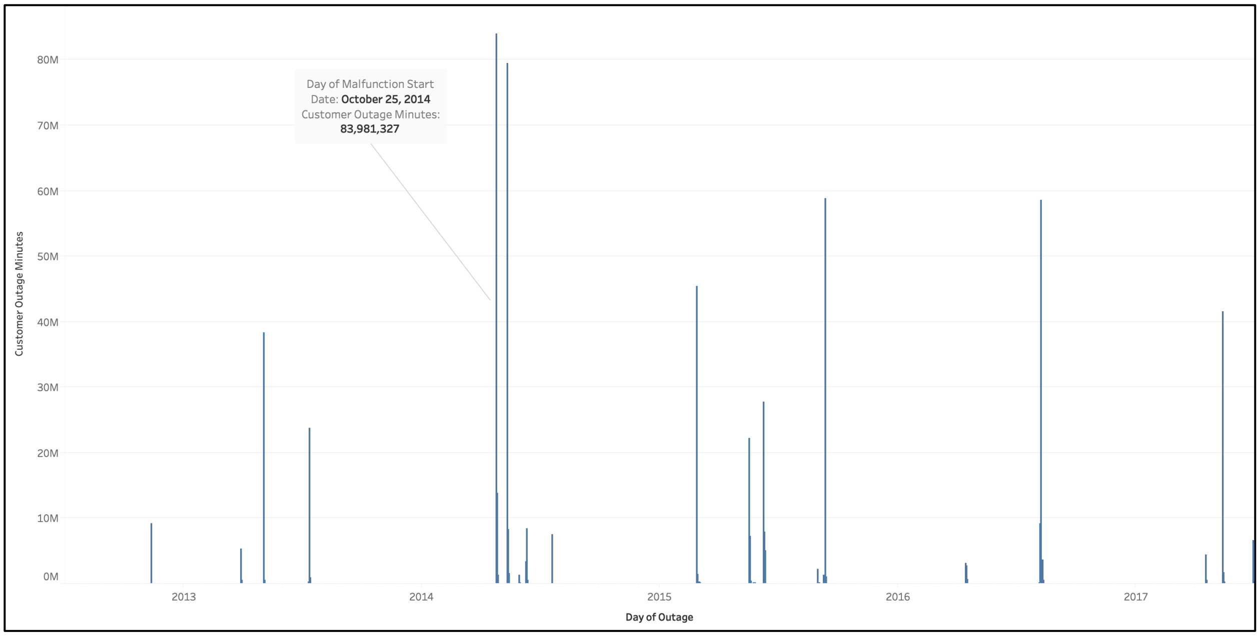

Figure 7: Customer Outage Minutes by Day

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Customer Outage Minutes	79	1,728.00	83,981,327.00	609,283,305	7,712,446.90	17,342,198.54

Table 3: Descriptive Statistics for Customer Outage Minutes by Day

Figures 8 and 9, analyze COMs by meteorological season. As a reminder, each meteorological season spans three months: Spring (March-May), Summer (June-August), Autumn (September-November), and Winter (December-February.) Over the five-year study period, Autumn has the highest total COMs with 320,505,248 minutes and Summer has the lowest total COMs with 46,758,528 minutes. Figure 9 specifically examines seasonal COMs by each of the five years in the study. While outages occur every Autumn, the other seasons do not have outages on a consistent annual basis. In fact, during the five year study period, Summer only has outages during 2015. Table 4 shows the descriptive statistics for seasonal COMs. Although Spring has the highest COM mean, the number of outages (N=597) is relatively small compared to the number of outages that occurred in the Autumn and Winter.

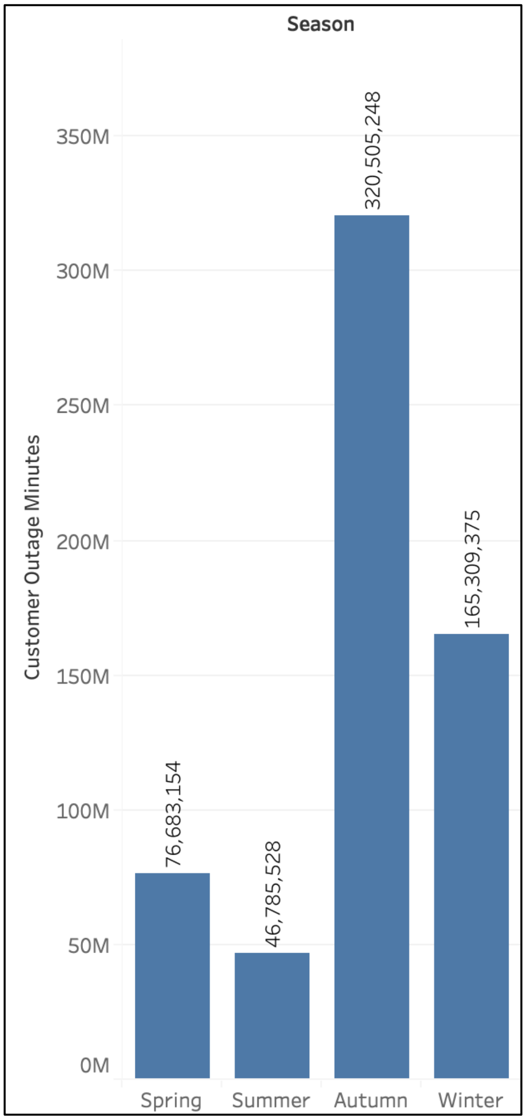

Figure 8: Customer Outage Minutes by Season

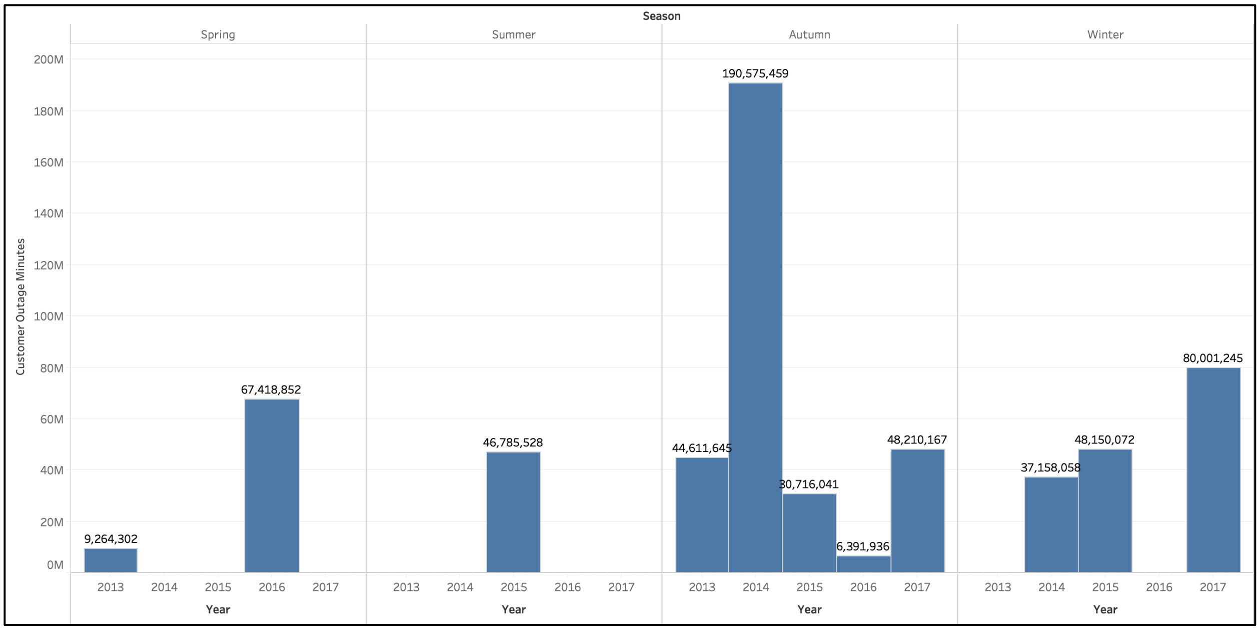

Figure 9: Customer Outage Minutes by Season and Year

Season	Mean	N	Std. Deviation	Sum	Minimum	Maximum
Spring	128,663.01	596	353,882.38	76,683,154	22	3,022,205
Summer	117,847.68	397	389,185.56	46,785,528	8	4,467,463
Autumn	124,710.21	2,570	436,060.29	320,505,248	6	7,967,166
Winter	93,289.72	1,772	231,032.06	165,309,375	11	2,802,752
Total	114,204.93	5,335	367,069.35	609,283,305	6	7,967,166

Table 4: Descriptive Statistics for Customer Outage Minutes by Season.

Given the temporal variations in COMs on a daily and seasonal basis, it is imperative to examine the spatial dimension of these outages as well. Figure 10 portrays COMs by individual substation. PSE operates 118 substations across King County. The magnitude of outages at the substation level vary considerably during the study period. Substation ID 112 – located in Kenmore, WA – has the highest COMs at 31,158,407 total minutes between 2013 and 2017. The mean COMs for substations is 5,163,418 (Table 5).

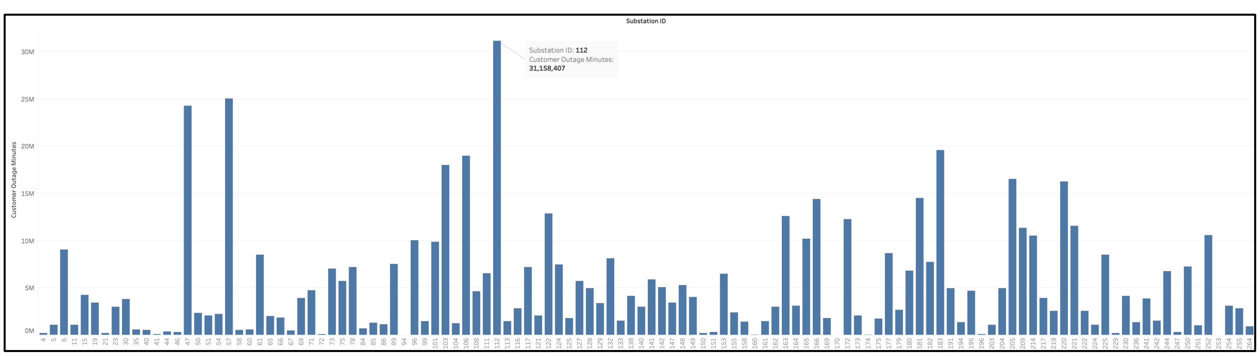

Figure 10: Customer Outage Minutes by Substation

	N	Minimum	Maximum	Sum	Mean	Std. Deviation
Customer Outage Minutes	118	3,625.00	31,158,407	609,283,305	5,163,417.84	5,746,205.41

Table 5: Customer Outage Minutes by Substation

Overall, these descriptive results indicate that there are considerable spatial and temporal variation of customer outage minutes from 2013 to 2017. Space and time are key components to understanding the functional performance of the PSE electric power system in King County. Next, this study examines whether these observed spatiotemporal outage patterns are in fact statistically significant and where clustering occurs.

3.2. System Performance

3.2.1. Global Pattern Analysis

Results from the Moran's I global pattern analysis – Moran's I Index and z-score – are presented in Table 6. The global pattern analysis examines each spatiotemporal element for spatial autocorrelation. The analysis finds that substations with similar customer outage minutes are significantly clustered together. There is less than a 1% chance that the features are randomly distributed across the study area ($p < .01$). Although all spatiotemporal elements are significantly clustered, the Moran's I Index and Z-score statistics indicate that COMs during Spring are most significantly clustered, whereas COMs during Winter are least significantly clustered. Overall, global pattern analysis reveals that substation locations are a significant variable in predicting the magnitude of electric power outages on a seasonal basis.

	Statistic	Total	Spring	Summer	Autumn	Winter
Substations	Moran's I Index	0.277	0.337	0.191	0.172	0.161
	Z-score	9.571	12.277	8.571	6.135	5.771

Table 6: Global Pattern Analysis Results

3.2.2 Local Pattern Analysis

The results of the local pattern analysis using Getis-Ord Gi* (hot spot) analysis are shown in Figures 11 - 15. Figure 11 represents substation COM clustering for all seasons during the study period. This study finds that high COM values are significantly clustered around Bothell and Woodinville in northern King County at a 99% confidence level. Less significant (90% confidence level) but still high COM clustering is located near Issaquah and Sammamish. Low COM values are significantly clustered around Kent, SeaTac, and Renton as well as Bellevue at a 99% confidence level.

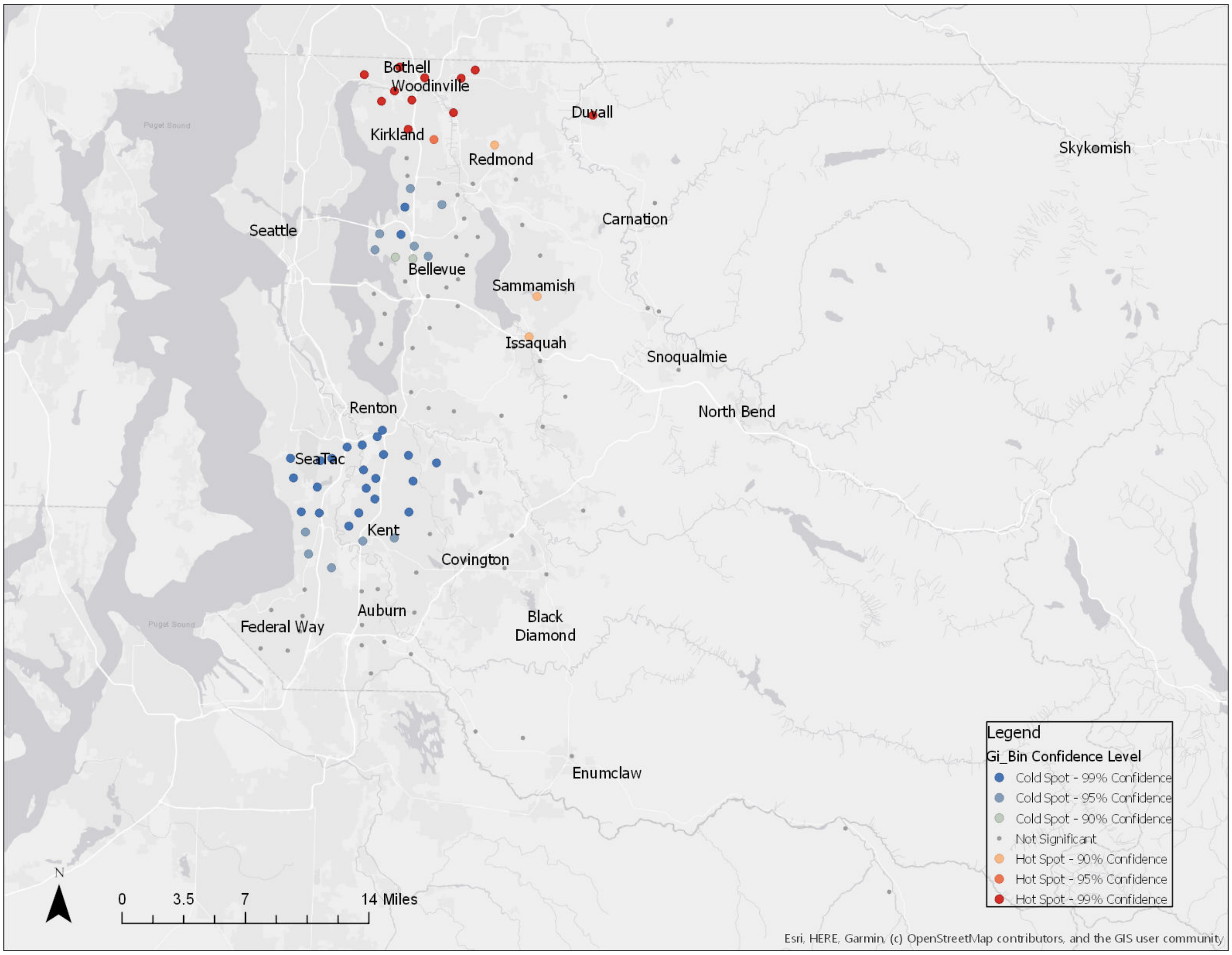

Figure 11: Getis-Ord Gi* Local Pattern Analysis Results: 2013 to 2017

Figures 12, 13, 14, and 15 show COM high/low value clustering for Spring, Summer, Autumn, and Winter respectively. During the Spring season (Figure 12), high COM values are significantly clustered around Both and Woodinville at a 99% confidence level. Low COM values are less significantly (90-95% confidence level) clustered around Kent, SeaTac, and Renton. During the Summer season (Figure 13), high COM values are significantly clustered around Bothell and Woodinville. There is no clustering of low COM values. During the Autumn season (Figure 14), high COM values are significantly clustered around Bothell, Woodinville, and Sammamish at a 90-95% confidence level. Low COM values are significantly clustered around Bellevue, Kent, SeaTac, and Renton at a 99% confidence level. During the winter season (Figure 15), high COM values are predominately clustered around Issaquah and Sammamish at a 95-99% confidence level. There is also high COM value clustering (95% confidence level) near Bothell and Black Diamond. Low COM values are significantly clustered around Kent and Renton at a 99% confidence level. Less significant (90-95% confidence level) low value COM clustering is found near Bellevue.

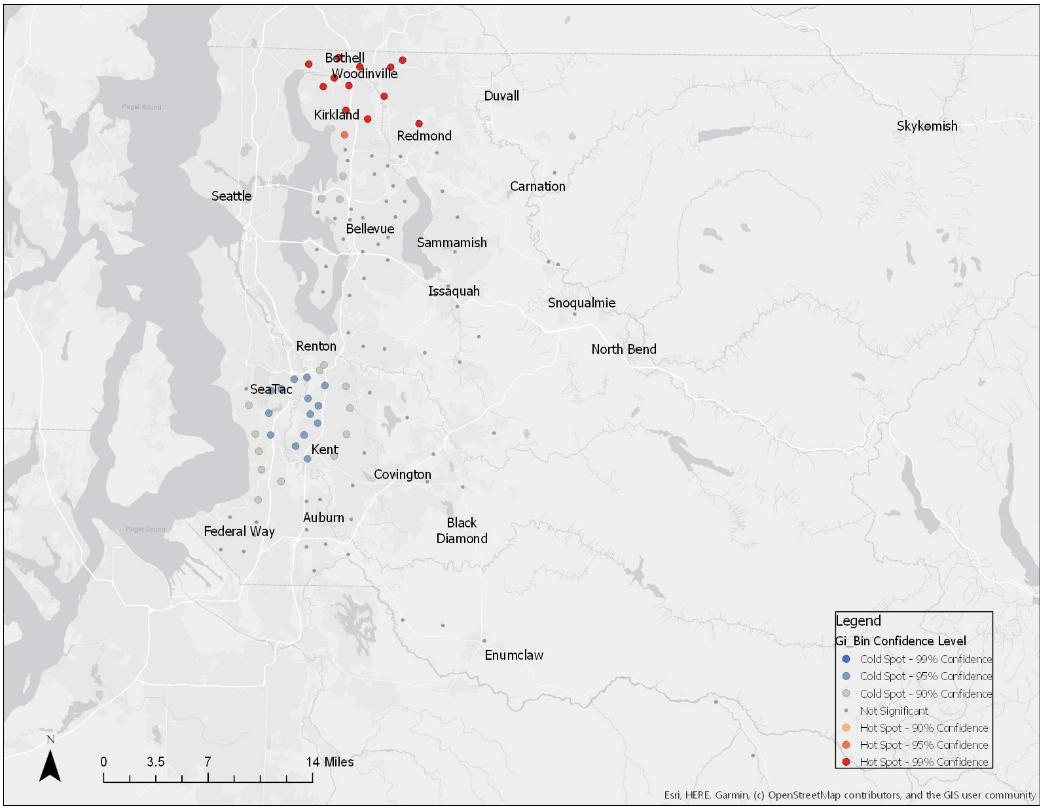

Figure 12: Getis-Ord Gi* Local Pattern Analysis Results: Spring 2013 to 2017

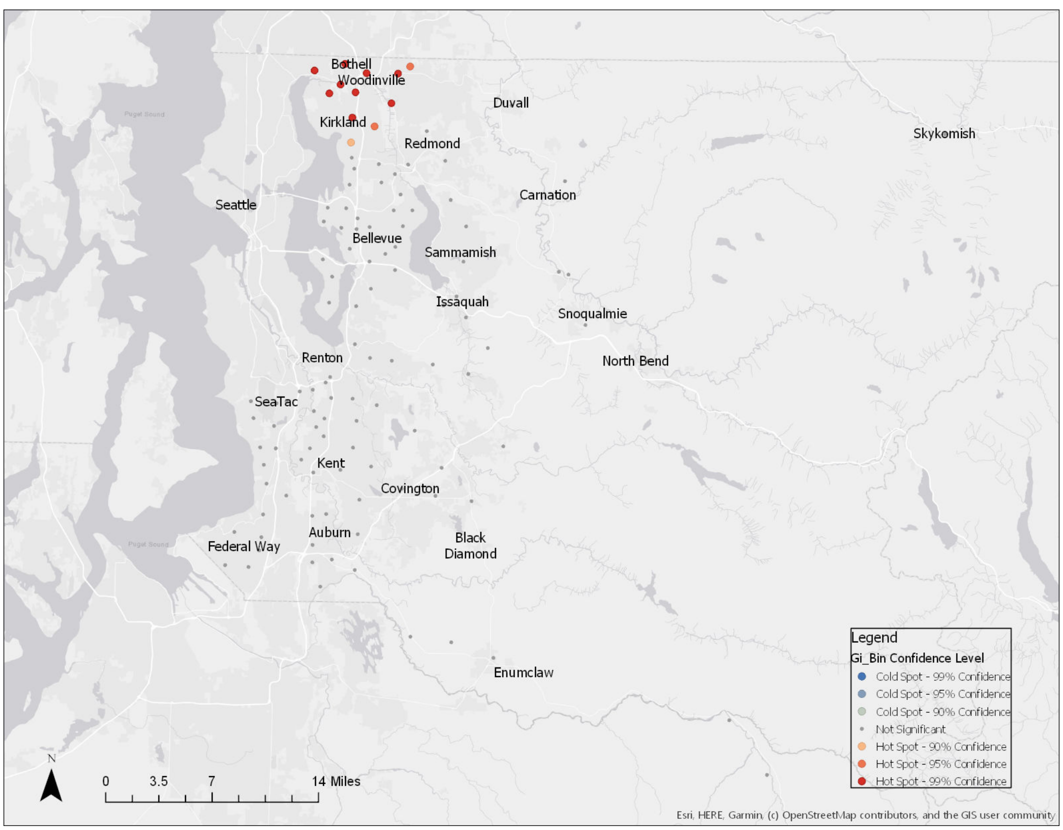

Figure 13: Getis-Ord Gi* Local Pattern Analysis Results: Summer 2013 to 2017

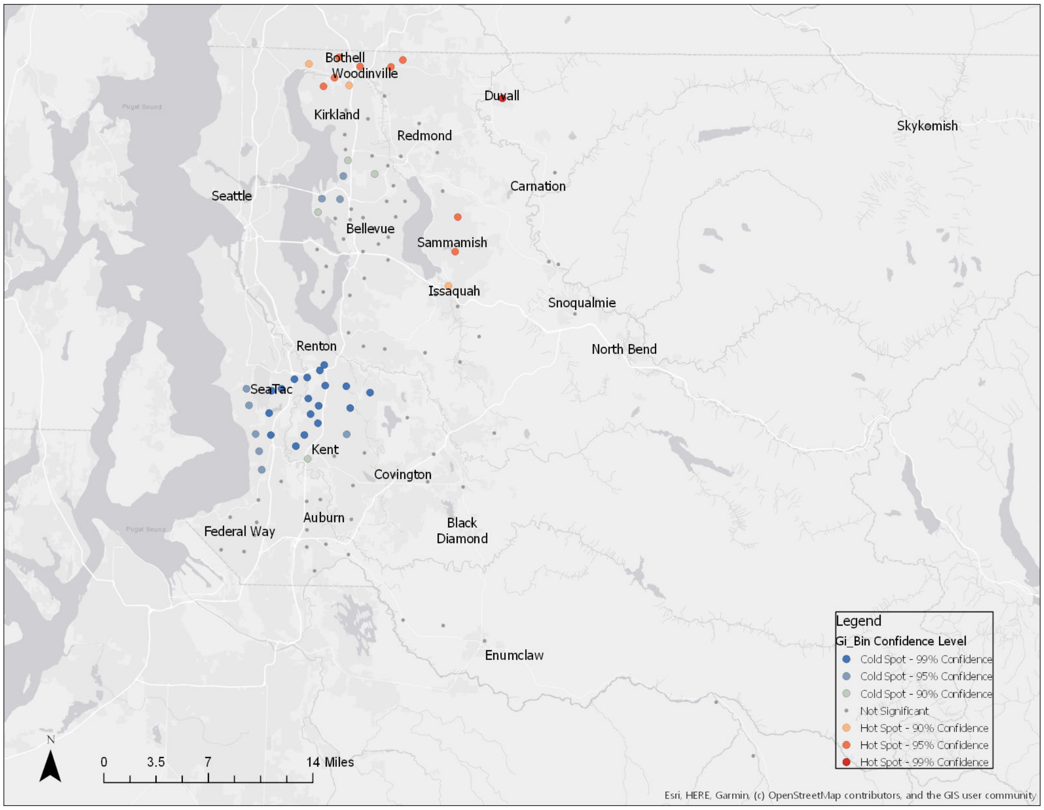

Figure 14: Getis-Ord Gi* Local Pattern Analysis Results: Autumn 2013 to 2017

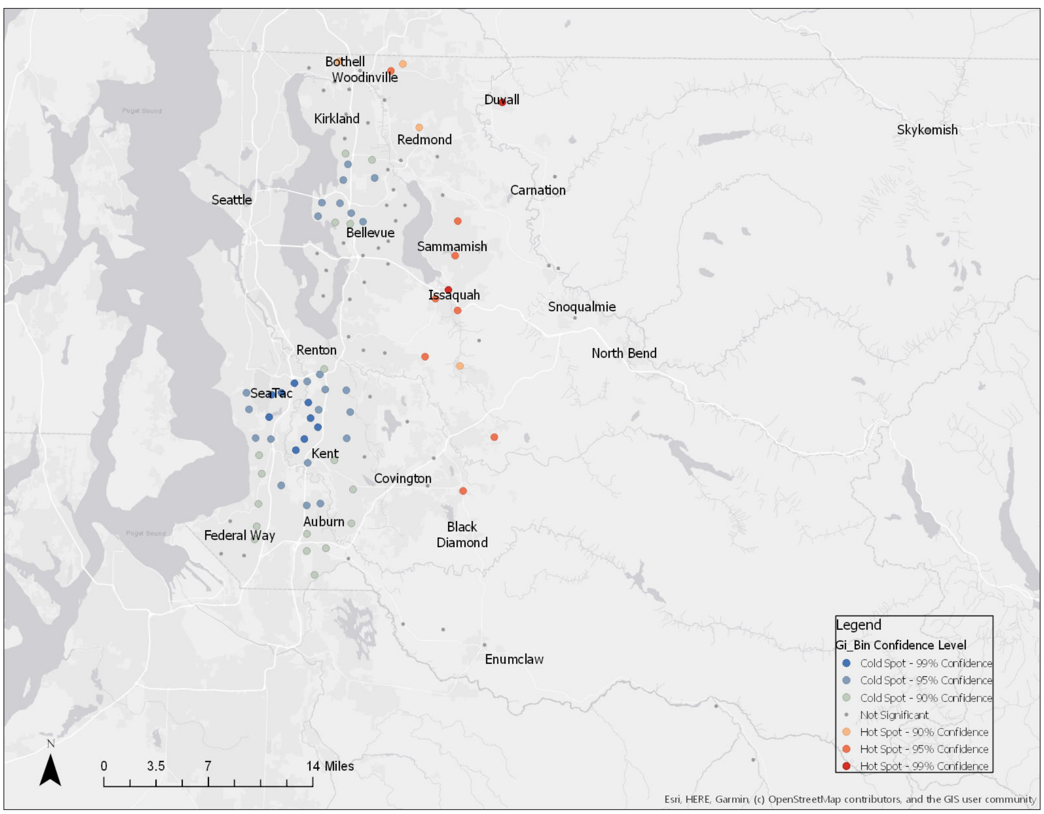

Figure 15: Getis-Ord Gi* Local Pattern Analysis Results: Winter 2013 to 2017

When comparing the seasonal results of the local pattern analyses, this study finds that substations with high COM values are consistently clustered near Bothell and Woodinville during all four seasons. Aside from Summer, substations with low COM values are consistently clustered near Kent, SeaTac, Renton and to a less significant degree Bellevue. High/low COM value clustering is not observed near the cities Enumclaw, Federal Way, Mercer Island, or Newcastle during any season. Seasonal anomalies are also observed. For example, high value COM clustering is observed for substations near Black Diamond during Winter only.

It is important to note that some of the observed results may be attributed to the temporal distribution of outage events. Most noticeably, during the study period – 2013 to 2017 – Spring outages occurred in 2013 and 2016 only while Summer outages occurred in 2015 only. Thus, when compared to Autumn or Winter, the Spring and Summer datasets have a fewer number of observed outages and lower COM totals (Table 4). While there is still significant spatial clustering during these periods, the outage magnitudes – in terms of COM – cannot be compared if only examining the local pattern analyses and not considering the descriptive statistics and overall data distribution as well. The substations where no pattern of COM clustering is observed either have fluctuating COM values or the fixed distance band – defining the conceptualization of spatial relationships – is too small to capture neighboring substations. Both cases require further exploration since fluctuating COM values at the substation level are still indicative of system functionality and geographically isolated substations provide critical electric power service.

3.2.3 Space Time Cube

Figure 16 shows the results of the Space Time Cube (STC) Emerging Hot Spot Analysis, based on Getis-Ord Gi*, for customer outage minutes at the substation level from 2013 to 2017. This analysis uses months as the temporal unit of aggregation (i.e. time-step interval) for outage events. Figure 16 identifies trends in clustering of COMs in a 2D map. There are 17 possible pattern types that can be identified using the Emerging Hot Spot Analysis. In this analysis, only sporadic hot spot clustering is identified in the areas primarily surrounding Bothell, Issaquah, Sammamish, and Woodinville. According to ESRI documentation, Sporadic Hot Spot clustering is defined as: "A location that is an on-again then off-again hot spot. Less than ninety percent of the time-step intervals have been statistically significant hot spots and none of the time-step intervals have been statistically significant cold spots" (ESRI 2019). Table 7 lists those substations where sporadic clustering is observed. Of the 118 PSE substations in King County, 19 are identified as sporadic hot spots. Substation ID #'s 47, 103, 122, 163, 166, 250, and 252 have the highest time-step interval significant percentages at 18.333%.

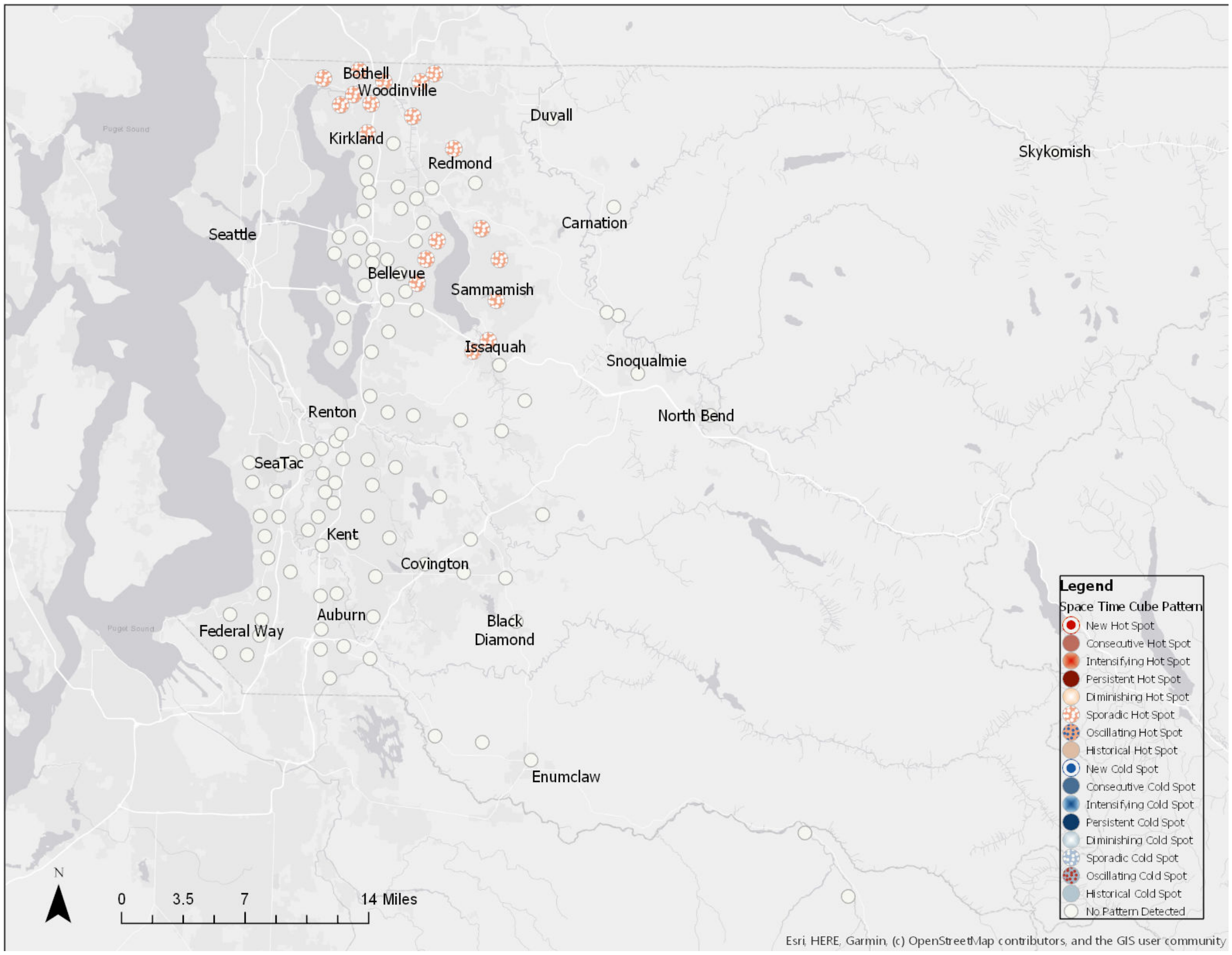

Figure 16: Space Time Cube 2D Emerging Hot Spot Analysis Result: 2013 to 2017.

Substation ID	Pattern Type	Percent Significant	Location (City)
47	Sporadic Hot Spot	18.333	Woodinville
103	Sporadic Hot Spot	18.333	Woodinville
122	Sporadic Hot Spot	18.333	Woodinville
163	Sporadic Hot Spot	18.333	Bothell
166	Sporadic Hot Spot	18.333	Bothell
250	Sporadic Hot Spot	18.333	Bothell
252	Sporadic Hot Spot	18.333	Bothell
106	Sporadic Hot Spot	16.666	Kenmore
108	Sporadic Hot Spot	16.666	Kirkland
6	Sporadic Hot Spot	13.333	Redmond
112	Sporadic Hot Spot	13.333	Kenmore
85	Sporadic Hot Spot	11.666	Issaquah
179	Sporadic Hot Spot	10	Bellevue
181	Sporadic Hot Spot	10	Sammamish
111	Sporadic Hot Spot	8.333	Redmond
121	Sporadic Hot Spot	8.333	Bellevue
180	Sporadic Hot Spot	8.333	Issaquah
183	Sporadic Hot Spot	8.333	Sammamish
205	Sporadic Hot Spot	6.666	Sammamish

Table 7: Space Time Cube Emerging Hot Spot Results

Figure 17 identifies the same overall trends in clustering of COMs at the substation level, but in a 3D representation. Figure 17 shows the high/low COM value clustering of individual time-steps from which the Figure 16 Emerging Hot Spot analysis pattern types are derived. The sporadic hot spots identified in Figure 16 are now more evident in the 3D representation. As already noted, clustering of high COMs values primarily occurs in the norther portion of King County and around Lake Sammamish. Figure 17 shows that these hot spot clusters are not continuous in time. Large time-step intervals appear between significant high COM value clusters (>90% confidence level), thus highlighting the sporadic nature of the hot spots. It also important to note that even substations where no pattern is detected in Figure 16, hot spot clusters are still observed in some of those substations in Figure 17. The occurrence of those hot spots, however, is too infrequent and, therefore, does not meet the thresholds established by the Emerging Hot Spot analysis to be identified as a space-time pattern. For example, high COM value hot spots are observed in southern King County, near Federal Way. These hot spots, however, do not occur frequently and, therefore, are not considered a significant spatiotemporal cluster when the entire STC study area and period is examined.

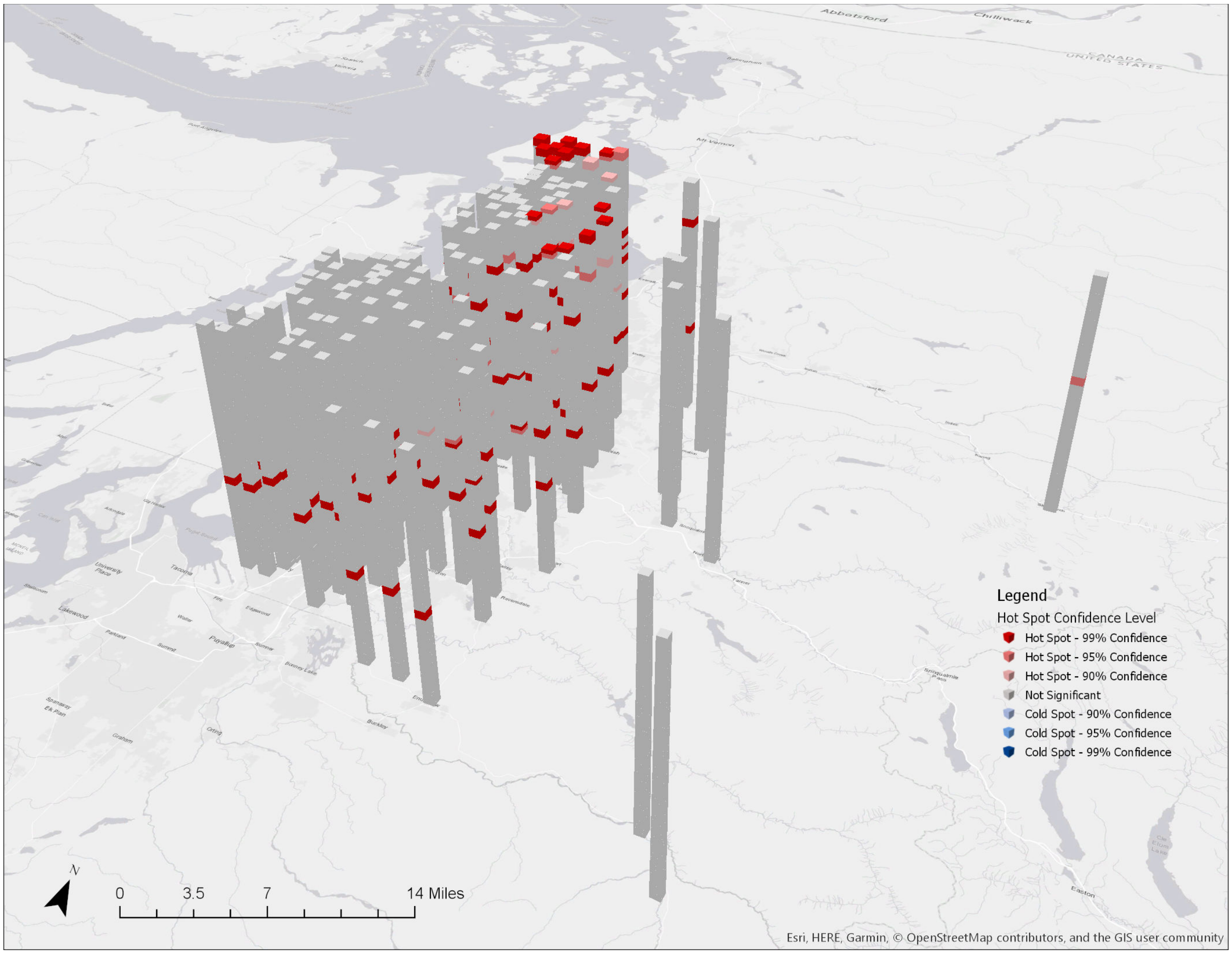

Figure 17: Space Time Cube 3D Emerging Hot Spot Analysis Result: 2013 to 2017.

Unlike the spatial pattern analysis discussed in section 3.3, outage data for the STC pattern analysis is only analyzed as a complete time series (i.e. data is not separated into seasonal categories). Features or bins within the STC cannot be empty. They must be filled with a value. If a bin contains a null value, then the entire location is excluded from analysis. Separating the dataset into seasons and, by extension, removing specific bins creates artificial temporal clusters in the data that will invalidate the results of the Emerging Hot Spot Analysis. When attempting to understand spatiotemporal trends then, all locations at each time-step interval must be included in the analysis. This allows substations with fluctuating high/low COM values to be observed more easily even if no overall pattern is detected.

Overall, the results of both the spatial pattern analysis and the STC pattern analysis indicate that substations with high customer outage minutes (COMs) are clustered in the areas around Bothell, Woodinville, and Lake Sammamish during all four seasons. The STC analysis shows that these clusters, while statistically significant, are sporadic and occur infrequently throughout the 2013 to 2017 study period. The spatial pattern analysis also indicates that low COMs are clustered in the areas surrounding Kent, SeaTac, and Renton for the entire study period. The STC pattern analysis does not find any significant clustering of low value COMs. Reasons for this discrepancy are not yet clear but may be attributed to the temporal unit of aggregation. To further investigate the impact that the time-step interval has on STC pattern analyses, sensitivity tests should be conducted whereby different time-step intervals are used as the basis of the STC development.

4. Discussion

Resilience is a concept that is defined by spatiotemporal variation and functional performance (Kowalski 2019). Thus, the first phase in any systems analysis is to assess how the system functions under normal operating conditions and during periods of stress across spatial and temporal scales. This section discusses 1) the advantages and limitations of the spatiotemporal models presented in this study and 2) how the results of this study are used to identify and assess broad patterns in functional performance and, ultimately, resilience associated with storm events.

4.1 Spatiotemporal Models

There is a significant range of biophysical, technical, economic, and social/political variables that influence the performance of electric power systems. The spatial and temporal data collected about the PSE electric grid and its response to storm events provides a broad representation of the system under stress. Key elements of the electric grid, including substation locations, service area boundaries as well as outage magnitudes are identified in this study. Notably, however, many elements of electric power systems are not included in the models due to data limitations. These include, for example, generation units, transmission and distribution lines, and customer load profiles. Although this level of detail is suitable for an initial performance assessment, modeling the precise impacts that resilience, or lack of resilience, will have on the production, distribution, and consumption of electricity will require significantly more detailed modeling approaches.

Spatial pattern analyses and space-time cube (STC) pattern analysis are used to examine patterns of functional performance in space and time. Both process models use a step-wise approach, in which customer outage minutes at the substation scale are aggregated into distinct time-steps over the five-year study period. The process models, therefore, are semi-dynamic, characterizing the spatiotemporal behavior of functional performance. Although both process models use a step-wise approach, the models differ in how time is treated and integrated with spatial data.

Traditional spatial analysis treats time as an attribute. Thus, in the first pattern analysis presented in this study, outage events are temporally aggregated together based on nominal attribute data, specifically meteorological seasons. In the second analysis – using the STC – time is treated as a fundamental property. While events or phenomena can still be aggregated to different temporal scales, those temporal aggregations become properties of the STC and not just attribute data. Because time, along with space, is embedded within the data structure – as a netCDF data cube – the spatiotemporal trajectories of phenomena, like outage events, are examined more easily within one analytical environment. The full extent of the pattern can be observed. For example, the use of the STC pattern analysis in this study allowed for the discovery that high COM values, while clustered in specific substations, are in fact sporadic throughout the study period. The 3D visualization of the STC hot spot analysis (Figure 17) shows exactly where in time and space these clusters occur and, just as importantly, where no pattern is detected. In general, the spatial analysis highlights more temporal variability in the clustering of COM values than the STC analysis. This may be due to the relative lack of observed outages during the Spring and Summer seasons.

These analytical models also have a couple of limitations. First, the available dataset and subsequent analysis only captures a small portion of the PSE electric power system functionality, namely customer electric outages. Second, functional performance of the PSE system is analyzed with respect to general storm-related disturbances (Folke et al. 2010; Walker and Salt 2012). There is no differentiation, for example, between wind, ice, or flood disturbances. Therefore, functional performance is based on a limited view of electric grid performance in order to 1) accommodate the available data and 2) reduce model complexity (Kwasinski 2016). For a preliminary assessment this is the most practical approach, where it is not yet feasible to model a wide range of technical, economic, and environmental variables without first understanding how the system broadly functions.

4.2 Functional Performance and Resilience

Using data collected from the representation model and information gained from the process model, it is possible to evaluate the performance of the PSE electric grid to disruptions. These events are characterized as low-probability, high-consequence disruptions to the electric grid. The spatiotemporal pattern models of customer outage minutes indicate that substations and, by extension, customers in the PSE service territory experience significant differences in functional performance of the electric grid. As a reminder, although the outage data is aggregated to the substation scale for the purpose of spatial analysis, specific outage events are recorded at the circuit level. These outage events are, therefore, implicitly measuring the failure or tripping thresholds of electric circuits on the distribution grid. While the current dataset does not indicate what those failure thresholds are, degraded functional performance of the distribution system places variable load demands on substations. Overloaded substations have a higher probability of failure, which can lead to cascading electric grid failures (Zhang and Yagan 2016).

Overall these pattern models indicate heterogeneity in the functional performance of the PSE electric grid in both space and time. The observed heterogeneity illustrates the importance of applying integrated spatiotemporal analytical approaches when examining electric power systems by demonstrating that the relation between geography, time, and system performance is significant across all three dimensions. Excluding one of these dimensions from analysis would lead to an incomplete understanding of the impact that storm events have on the electric grid. For example, when time is excluded from the analysis (Figure 11), there is no indication that the observed clusters fluctuate through time. This is not to say that the results are inaccurate but rather including the temporal dimension in the analysis (Figures 16 and 17) provides more insightful understanding. When both the spatial extent and temporality of these outages are taken into account, we see that substations with high COMs cluster sporadically over the study period.

The observed spatiotemporal heterogeneity of functional performance raises three important questions when evaluating the performance management of the PSE electric grid.

First, do customers equitably incur the costs of these service disruptions or are the costs inequitably distributed? Electric utilities in the U.S. have a regulatory responsibility to meet specific performance and quality standards. While the overall utility grid might meet those standards, there could be customers located in specific geographic areas, as demonstrated in this study, that experience an unsatisfactory level of performance on a more frequent basis (Maliszewski and Perrings 2012). The aggregation of performance data to the utility's entire electric power system might, therefore, obscure more localized performance issues. Second, what are the underlying variables that cause outages to cluster? For the PSE electric grid in King County, WA this study demonstrates that high magnitude outage events are not randomly distributed across substations. Therefore, a causal relationship between space, time, and outages could be explored.

To answer these two questions, more granular spatial data is needed, particularly at the distribution system scale. Understanding the spatiotemporal extent of these outages and the association between any explanatory variables will require higher resolution data and functional performance models. Examples of additional data include the geographic location of circuit failures, type of customer affected (e.g. residential vs. commercial), and weather data. This means going beyond identifying the proximate outage cause and attempting to understand why the disruptions are occurring. If downed trees are causing the majority of distribution line failures, system operators must then identify why vegetation is more problematic in these specific areas. Does the utility need to dispatch more resources for vegetation management or is there an environmental variable, such as soil composition and slope angle, that leads to a more unstable surface? Do operators need to increase the robustness of overhead distribution lines to wind storms or is distribution line redundancy required? Ultimately, practitioners need to know not only the cause of disruptions but also how to improve functional performance.

The last and perhaps most important question this study raises is, are the observed trends in functional performance indicative of decreased PSE electric grid resilience to storm events? Although functional performance is diminished, it is important to know if those performance measures are within a tolerable threshold for system operators. If performance is not within a tolerable threshold, then the ability of the electric grid to respond and recover from adverse events (i.e. resilience) could be impaired and, therefore, require hardening or operational performance upgrades (Espinoza et al. 2016; Panteli, Mancarella, and Trakas 2017). Information is needed concerning functional performance targets and thresholds of the system. Above or below this specific value, as quantified by the metric, functional performance is no longer satisfactory (Walker and Salt 2012; Schultz and Smith 2016). Functional performance thresholds, therefore, quantify critical points at which disruptions may trigger a degradation or collapse of the system below a satisfactory level of functional performance. Thresholds establish minimum or maximum values for performance (Molyneaux et al. 2016). A functional performance target is the preferred level of functional performance for the objective. Whereas a threshold is the minimum level of performance, a target is the ideal level of performance (Keeney 1992).Therefore, the exact type of performance upgrade or resilience strategy cannot be defined until functional performance is evaluated against performance thresholds and targets.

The performance assessment presented in this study demonstrates that certain areas experience higher magnitude outage events. Given that the available dataset only captures a narrow range of the PSE electric power system functionality, this study is best situated as a preliminary assessment. The next step in the performance assessment workflow is to develop more detailed representation and process models, whereby the dynamic interactions between system components and disruptions are assessed according to defined thresholds. Researchers can then evaluate how the system performs according to the expectations of system operators and other stakeholders.

5. Conclusions

This paper examines the spatiotemporal performance patterns of the PSE electric grid in King County, WA. Patterns of degraded functional performance across space and through time are analyzed using customer outage minutes as the performance metric. The study finds statistically significant clustering of high and low value customer outage minutes at the substation scale. Substations with high customer outage minutes are clustered in the areas around Bothell, Woodinville, and Lake Sammamish during all four seasons. The Space Time Cube analysis shows that these clusters, while statistically significant, are sporadic and occur infrequently throughout the 2013 to 2017 study period. Overall, the pattern analyses indicate heterogeneity in the functional performance of the PSE electric grid in both space and time. Thus, customers within the PSE service territory experience significant differences in functional performance of the electric grid.

The preliminary performance assessment identifies substations and the surrounding service areas of the PSE electric grid where functional performance is diminished. Future research must now examine why functional performance is degraded in these areas and also if this lack of functional performance comprises the electric grid’s response to natural hazards. Such assessment models, however, require higher resolution data about electric grid infrastructure, performance, long-term targets. Each component of the energy system – production, distribution, and consumption – is associated with particular data needs. This includes energy potential, environmental restrictions (e.g. slope, land cover), and technical/economic factors (e.g., distance to demand, land ownership) (Bridge et al. 2013, Calvert 2015, De Boer and Zuidema 2015). Once a comprehensive performance assessment is completed, practitioners can then explore possible intervention strategies to increase the resilience of the system to future disruptions.

In practice, however, workflow processes are rarely as structured. This is especially true in an energy system management context where decision-making often involves highly complex and dynamic problems (Keeney 1996, Dietz 2003). Nonetheless, incorporating such workflow processes, as demonstrated in this paper, will help system operators and other practitioners choose the best management strategy for a given problem, such as increasing electric grid resilience. When dealing with data at multiple spatiotemporal scales, this can dramatically improve our ability to manage data, share information, model systems, develop management scenarios, evaluate tradeoffs, and overall, manage stakeholder participation in a straight forward manner.

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Chapter Four

Power Outages and Social Vulnerability:

A Case Study of King County, WA

1. Introduction

Natural hazards, such as earthquakes, floods, and wildfires, can have a range of significant social, economic, political, and biophysical impacts. These may include damage to key infrastructure (e.g. roads and medical facilities), destruction of residential and commercial structures pollution of surface water, and disruption of electric power service (Heinz Center 2015). Hazards can either be chronic with incremental impacts, like climate change, or sporadic with catastrophic impacts, like earthquakes (Cutter 1996).

Traditionally, disaster management planning primarily focuses on infrastructure vulnerability. Social vulnerability, however, is a critically important component of disaster management planning. Research shows that poor communities are more vulnerable before, during, and after catastrophic events. Disaster management plans, therefore, must identify socially vulnerable communities so the specific needs of those communities can be appropriately addressed in the planning process (Flanagan et al. 2011; 2018).

Social vulnerability is defined as the social, economic, and demographic factors that influence a community's susceptibility to harm from a disaster (Cutter, Boruff, and Shirley 2003; Flanagan and Hallisey 2013; Flanagan et al. 2018). Social vulnerability analysis, therefore, is an attempt to understand the underlying, and often unaddressed, factors that make certain groups in specific geographic locations more or less susceptible to harm from a give hazard (Heinz Center 2015). Given the inclusion of economic factors in this definition, it is important to note that the indices discussed in this paper measure socio-economic vulnerability, not just social vulnerability. Nonetheless, this paper will still use the term social vulnerability for consistency with past research.

In addition to identifying socially vulnerable communities, researchers must also examine if those communities are being unequally impacted by specific hazards or catastrophic events. Performance degradation of key services - caused by natural and anthropogenic hazards such as hurricanes or cyberattacks - can have profound impacts on all communities. Electric power outages are one example of a potentially catastrophic event that could cause undue harm to socially vulnerable communities due to a performance degradation or disruption in a key service (i.e. commercial and residential electricity). Impacts can include limited access to health services, water service interruption, and communication disruption.

From a disaster management planning perspective, it is particularly important to examine the geographic or spatial distribution and patterns of service disruptions and socially vulnerable communities. Detailed quantitative analysis can attempt to investigate if outages are occurring with more significant frequency and greater magnitude within socially vulnerable communities and where those locations might be. As Flanagan and Hallisey (2013: 14) state, "Knowing the location of socially vulnerable communities, planners can more effectively target and support mitigation and response efforts."

This study examines the relationship between the performance of electric power systems exposed to unplanned storm disturbances and socially vulnerable populations in King County, WA. The primary objective is to develop an analytical model of the Puget Sound Energy electric power system in King County that analyzes the spatial patterns of power system performance in relation to socially vulnerable populations. The key research questions include 1) is there a relationship between social vulnerability and electric power outages and 2) if a relationship exists, how does this relationship spatially vary across King County?

2. Social Vulnerability

The construction of indices can help reduce complexity and reflect multidimensionality in models when observing phenomena by aggregating multiple variables or indicators into a single measure (Reckien 2018; Rufat, Tate, and Emrich 2019). To this end, various social vulnerability indices have been developed, starting in the late 1990's, to help increase the effectiveness of disaster management planning and emergency response to a range of natural hazards. The two most predominant social vulnerability indices are the Social Vulnerability Index (SoVI) developed at the University of South Carolina and the Social Vulnerability Index (SVI) developed at the U.S. Centers for Disease Control.

In developing SoVI, Cutter, Boruff, and Shirley (2003) identified 42 variables, obtained from the U.S. Census Bureau, that affect vulnerability to natural disasters in order to create the SoVI. These include, for example, age, gender, race, socio-economic status, infrastructure and lifelines, medical services, and social dependence. Principal component analysis was used to reduce the data to 11 factors that differentiated U.S. counties according to their social vulnerability. These 11 factor scores were then placed in an additive model to create the SoVI index score. Since then, Cutter and colleagues have refined the SoVI to only examine 29 socio-economic variables. Using principal components analysis, they identified 7 significant factors: race and class, wealth, elderly residents, Hispanic ethnicity, special needs individuals, Native American ethnicity, and service industry employment. With this method, each variable or factor contributes equally to SoVI. Positive scores indicate high levels of social vulnerability and negative scores indicate decreased social vulnerability. (Heinz Center 2015).

The CDC defines social vulnerability as the exposure of a community to human suffering and financial loss in a disaster (Flanagan and Hallisey 2013). The social vulnerability index (SVI) was created by the CDC's Agency for Toxic Substances and Disease Registry (ATSDR) to "help emergency response planners and public health officials identify and map communities that will most likely need support before, during, and after a hazardous event" (Agency for Toxic Substances and Disease Registry 2019). SVI is a deductive hierarchal index composed of four themes: socio-economic status, household composition, race/ethnicity/language, and housing/transportation. Each theme is composed of several census variables. SVI uses 15 variables to capture social, economic, and demographic characteristics that are associated with social vulnerability to a disaster. SVI is an additive model, whereby census variables are added together based on theme and then those themes are added together to form a single composite score. Census variables are chosen because census tract data is used for a variety of public policy and planning purposes. In addition, they are easy to understand and included in both the decennial U.S. Census of Population and Housing and the five year American Community Survey. A SVI database is available at https://svi.cdc.gov/data-and-tools-download.html. Researchers and disaster management planners have used the SVI and associated database to examine the social vulnerability of communities to a range of hazards and disasters. This includes fire outbreaks, heat-related mortality, and hurricanes (Flanagan et al. 2018).

Other indices that aim to measure social vulnerability include Baseline Resilience Index for Communities (BRIC), Community Disaster Reliance Index (CDRI), Resilience Capacity Index (RCI), and Social Vulnerability Profile (SVP) (Bakkensen et al. 2017; Rufat, Tate, and Emrich 2019). Overall, researchers use these social vulnerability indices and associated models to help disaster management practitioners respond to a range of hazards, including severe weather, hurricane wind and storm surge, river flooding, and earthquakes, by modeling potential impacts and resource allocation needs (Wex et al. 2014; Rufat, Tate, and Emrich 2019). The field of social vulnerability analysis and index construction continues to advance, however, more research has begun to focus on the limitations of such models (Fekete 2019).

The primary concern with social vulnerability indices is whether they correspond with post-disaster outcomes and, thus, whether the associated models are effective at measuring social vulnerability. To explore this, researchers have conducted both sensitivity and validity analyses using empirical data. Although this specific research focus is still growing, studies have generally found social vulnerability indices are extremely sensitive to construction methods. This may include variable selection, variable representation (e.g. absolute vs. proportional counts), and the standardization of variables (e.g. z-scores vs. ordinal ratings). Differences in the index construction method can ultimately result in large differences in the estimation and measurement of social vulnerability for the same study area (Jones and Andrey 2007; Schmidtlein et al. 2008; Reckien 2018).

Bakkensen et al. (2017) examines the empirical validity of five social vulnerability indices, including SoVI and SVI. Using regression analysis, they analyze social vulnerability against three post-disaster outcomes in the southeastern U.S.: property damage, fatalities, and frequency of disaster declaration. The study finds that SoVI is positively and significantly correlated to property damage and frequency of disaster declarations, while SVI is positively and significantly correlated to property damage and fatalities. In a similar validation study, Rufat, Tate, and Emrich (2019) examines the empirical validity of social vulnerability models using post-disaster data from Hurricane Sandy. They compare four social vulnerability models, again including SoVI and SVI, against FEMA outcome data, such as individual assistance program applicants and real property FEMA-verified losses. The study finds that the four models consistently identify the same geographic places as the most and least socially vulnerable. However, the explanatory power varies substantially across the models. SVI has the weakest explanatory power, whereas Social Vulnerability Profile (SVP), developed by the authors, is the only model with positive and significant relationships to all FEMA-measured Hurricane Sandy outcomes.

Research on the sensitivity and validity of social vulnerability indices clearly demonstrates that caution is needed when using indices to model social vulnerability for descriptive and/or explanatory purposes. This suggests that disaster management practitioners should evaluate the validity of specific indices against relevant disaster-related outcomes for their jurisdiction or area of interest before using those indices to model potential impacts or resource allocation needs. Nonetheless, it must be noted that researchers have examined only a small subset of disaster-related outcomes. Social vulnerability indices should not be abandoned due to these limitations but rather improved upon as more empirical data is available.

3. Methods

3.1 Study Area

King County is the most populous county in Washington State. It is defined as a metropolitan county according to the USDA but the county does contain urban, suburban, and rural communities. According to the 2010 census, King County has a population of 1,931,249 people. Puget Sound Energy (PSE) is the largest electric utility provider in King County and Washington State. Throughout the state, PSE provides electricity to more than 1 million customers (PSE 2019). The demographic and geographic composition of King County means that PSE must supply electricity to a wide range of customers over a geographically diverse service territory.

3.2. Data

3.2.1 Electric Power Outage Data

Electric power system outage data for King County were obtained from Puget Sound Energy (PSE). The dataset includes all PSE electric utility service areas within King County, WA from January 1, 2013 to December 31, 2017. In total, PSE provides electric utility service to 30 cities and townships, including unincorporated areas, within King County. The outage data spans five years, from 2013 to 2017. January 1, 2013 was chosen as the start date because that is when PSE implemented an automated data outage management system. The end date – December 31, 2017 – is the last year for complete data at the time of this study. This five-year period, therefore, represents the most recent, complete, and accurate outage data for PSE service areas in King Country, WA.

Outage data are recorded at the circuit level. Each data record represents a single circuit outage on the PSE distribution grid. Outages are recorded on a per day basis and have a temporal resolution of hours, minutes, and seconds. The outage database obtained from PSE contains attribute data for each outage event as well. This includes outage start date and time, duration, number of customers impacted, customer outage duration, reference circuit description, outage cause, equipment type involved in the outage, and storm category. Importantly, outage data includes both planned and unplanned outages. Over the five year period there were 30,416 planned and unplanned outage events recorded for PSE service areas in King County, WA.

The dataset provides four metrics for customer electric power service. They include the number of outages, outage duration, number of customers affected per outage, and customer outage minutes per outage. Of those four metrics, customer outage minutes (COMs) best captures the functional performance of the PSE electric grid since it takes into account the extent (i.e. number of customers affected) and duration of outages (Bakkensen et al. 2017). COMs are calculated by multiplying the number of affected customers by the duration of the outage. In this study, COMs is used to measure electric power outages across King County, WA.

For confidentiality reasons, the geographic locations of the circuits where the outages occurred are not provided by PSE. Instead, each outage event has an associated reference circuit description that contains a facility code for the substation that serves the circuit. Thus, outages are aggregated to the substation level (Figure 1). Substations, therefore, serve as the most detailed level of analysis for this study. To prepare the data for analysis, each outage record was first associated with its corresponding substation. As of 2017, PSE operates 118 substations in King County. Substation street addresses were geocoded in ArcGIS Pro using an address locator based on the King County, WA road network as the reference dataset. This provides the latitude and longitude of each PSE substation in King County, WA and, by extension, the geographic location of each aggregated outage record. Next, substation outages were aggregated to the zip code level to provide the same scale of analysis as the social vulnerability data. Finally, outages caused by storms were selected from the dataset using the storm category attribute. From 2013 to 2017, there were 5,335 storm-related outages in PSE service areas within King County.

Importantly, PSE service territory in King County includes zip codes without substations and therefore no available outage data. These zip codes are largely in rural areas with small populations and limited electric power system infrastructure. These zip codes are excluded from analysis. Including them in the study would have skewed the results, as the outage value would have been measured as zero when in fact there were likely outages in the zip codes at the circuit level. In total, 43 zip codes in King County are analyzed in this study.

3.2.2 Social Vulnerability Index

To examine social vulnerability, this study uses the Social Vulnerability Index (SVI) dataset from the U.S. Centers for Disease Control (CDC) (Agency for Toxic Substances and Disease Registry 2019). As seen in Table 1, the SVI is composed of four themes: socio-economic status, household composition, race/ethnicity/language, and housing/transportation. Each theme is composed of several census variables.

Table 1: Social Vulnerability Index themes and variables

SVI Theme	SVI Census Variable
Socio-economic Status	Below Poverty
	Unemployed
	Income
	No High School Diploma
Household Composition & Disability	Aged 65 or Older
	Aged 17 or Younger
	Civilian with a Disability
	Single-Parent Households
Minority Status & Language	Minority
	Speaks English “Less than Well”
Housing & Transportation	Multi-Unit Structures
	Mobiles Homes
	Crowding
	No Vehicle
	Group Quarters

This study generally follows the CDC's SVI computation methodology by ranking each census tract against each other on the 15 variables. Each tract receives a ranking for each census variable. Rankings are based on percentiles, with values ranging from 0 to 1. A higher percentile rank represents a greater social vulnerability. In addition, each of the four themes are ranked by summing the percentiles for the variables within each theme. An overall composite census tract ranking is obtained by summing the sums of each theme (Flanagan et al. 2011).

Despite SVI's poor performance in the Rufat, Tate, and Emrich (2019) study, this model is still chosen as a starting point for examining socially vulnerability in relation to electric power outages due to its prominence in the research literature and replicable index construction methodology. Furthermore, the FEMA outcomes Rufat, Tate, and Emrich (2019) examine do not include any indicators directly associated to electric power loss.

This study modifies the CDC's SVI methodology in one important way. It uses zip code data instead of census tract data as the spatial unit of analysis for social vulnerability. Zip code level data is used in order to match the spatial scale of the electric power outage data obtained from PSE. Therefore, this study could not use the CDC SVI's database. Rather, raw data pertaining to the 15 SVI variables was collected from American Fact Finder (https://factfinder.census.gov) using 5-year American Community Survey data from 2012 to 2017. All variables were transformed so that a higher value indicates a zip code with higher social vulnerability. Specifically, income was transformed to its inverse so a lower income value would indicate higher social vulnerability.

Overall, this study develops three analytical models at three different scales of SVI data aggregation. The first scale - Model 1 - models each of the 15 census variables. The second scale - Model 2 - models the four SVI themes. The last scale - Model 3 - models a single composite score for SVI. These three models increase in the level of data aggregation, moving from a low level of data aggregation by modeling 15 SVI census variables to a high level of data aggregation by modeling only a single SVI composite score.

3.3 Data Analysis

This study uses a combination of spatial analysis as well as descriptive and inferential statistics to examine the association between electric power outages and social vulnerability in King County, WA. Three global ordinary least squares (OLS) linear regression models are developed to test the relationship between the dependent variable - customer outage minutes (COMs) - and independent variable - SVI measures. Each model is specified by the following OLS regression equation:

$$Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_n X_n + \varepsilon$$

The models examine COMs in relation to the three scales of SVI analysis discussed in the previous section: census variables, themes, and composite score. The models analyze whether there is a statistically significant relationship between electric power outages and social vulnerability and if that relationship varies geographically. The regression models are developed and all analytic operations are performed using ArcGIS Pro 2.0 and IBM SPSS Statistics 25.

This study analyzes how well the three SVI models can predict COMs using global and local regression models. A global regression model provides one linear regression equation to represent the entire dataset, whereas local regression model - GWR - fits a regression equation to every feature in the data. Both models measure correlation and regression parameters. Correlation measures the strength of the relationship between two variables. It is a measure of the degree that two variables covary or how the values of any pair are similar. Pearson's r coefficient can range from -1 to 1. The value 1 indicates a perfect positive correlation, whereas the value -1 indicates a perfect negative correlation, and 0 indicates no relationship. Regression examines how much variation in the dependent variable (y) can be explained by the variation in independent variable (x). A simple regression, as used in this report, tries to fit a linear line through the data values to best minimize the residual values. The residual is the difference or error between the observed and predicted values. It is the amount of variable that the independent variable was unable to predict. The coefficient of determination (R^2) measures the quality of prediction or how much variability the model is able to predict. R^2 is a percentage, ranging between 0 and 1. Zero indicates a poor prediction and 1 indicates a good prediction.

After performing the linear regression analyses, this study then assesses the results of the models by examining the model performance, independent variables, model significance, stationarity, model bias, and residual spatial correlation. Within ArcGIS Pro 2.0., the Spatial Autocorrelation (Moran's I) tool is run on the regression residuals to determine if the residuals are spatially autocorrelated. Statistically significant spatial autocorrelation indicates that a key independent variable is missing and, thus, the model results are invalid. If the results of the regression analysis are in fact invalid, then a geographically weighted regression (GWR) analysis is conducted. A GWR model is a local linear regression model, as opposed to a global OLS regression model, that fits a separate regression equation to every feature (e.g. zip code) in the dataset.

It is important to note that this study does not normalize COMs or SVI data by population. COMs is not normalized by population because the PSE dataset did not include the total number of customers served in the utility's territory. While it is possible to normalize SVI by population, this study concludes that using gross SVI scores at the zip-code level is more appropriate for real-world disaster planning and management. Wex et al. (2014) and (Liu, Hu, and Li 2012) find that allocating and scheduling resources for natural disaster management should be partially based on the predicted destruction and severity level of the event. Communities with the highest SVI scores could theoretically require the most planning, management, and response resources. Gross SVI, therefore, more appropriately reflects the potential severity level of a power outage rather than SVI normalized by population.

4. Results

4.1 Spatial Distribution

From 2013 to 2017, there were 5,335 outage events within the PSE service territory in King County, WA. Figure 1 represents customer outage minutes (COMs) at the zip code level classified as quintiles. COM values are highest around the cities of Bothell and Woodinville in northern King County. Lower COM values center around Carnation, Snoqualmie, and North Bend and are attributed to smaller populations.

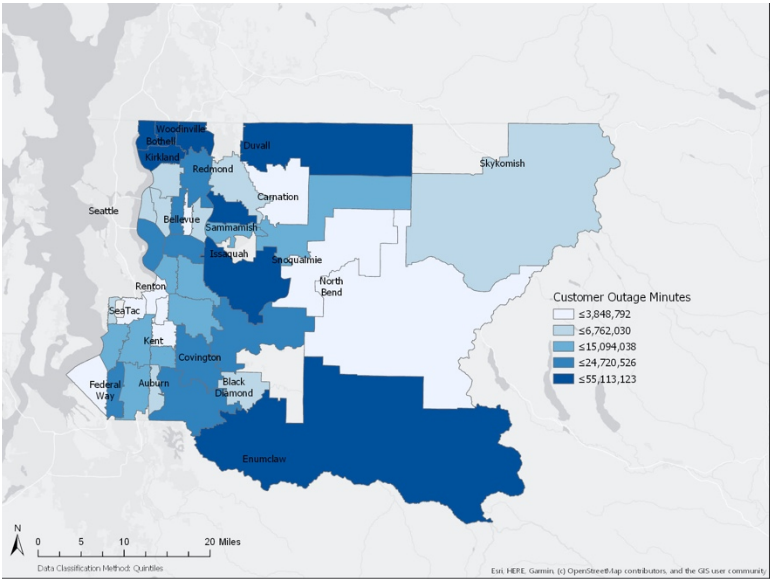

Figure 1: Customer Outage Minutes by Zip Code in King County, WA

Figures 2-5 represent the zip code rankings across King County for each of the four themes respectively: socio-economic status (Theme 1), household composition and disability (Theme 2), minority status and language (Theme 3), and housing and transportation (Theme 4). Across all four themes, the communities surrounding Auburn, Federal Way, and Kent are most vulnerable, whereas the communities around Carnation, Sammamish, and Snoqualmie are least vulnerable.

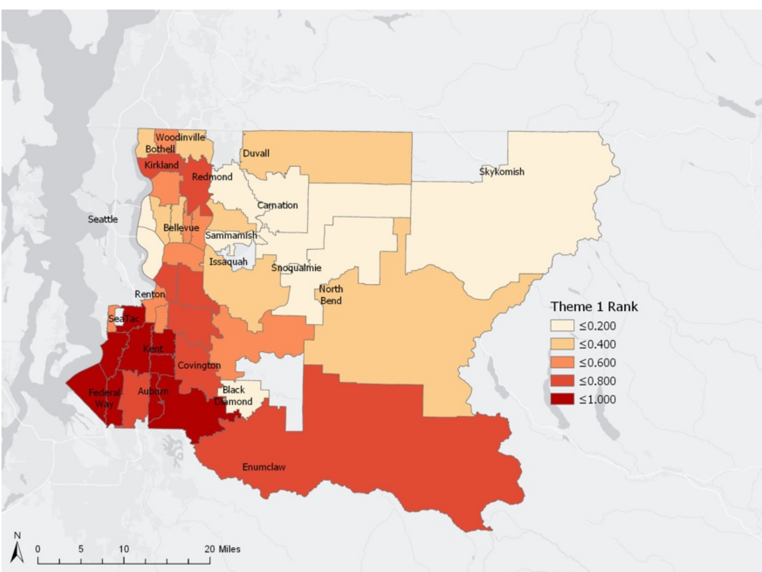

Figure 2: Socio-economic Status Ranking (Theme 1) by Zip Code in King County, WA

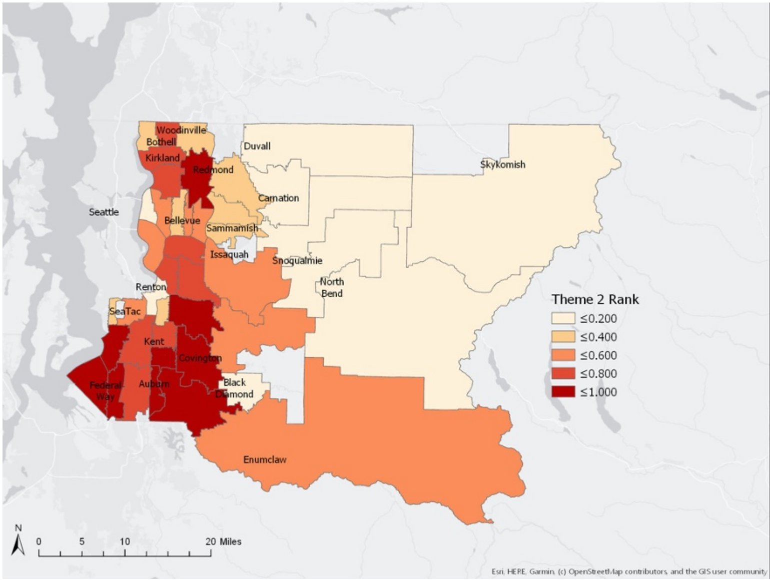

Figure 3: Household Composition and Disability Ranking (Theme 2) by Zip Code in King County, WA

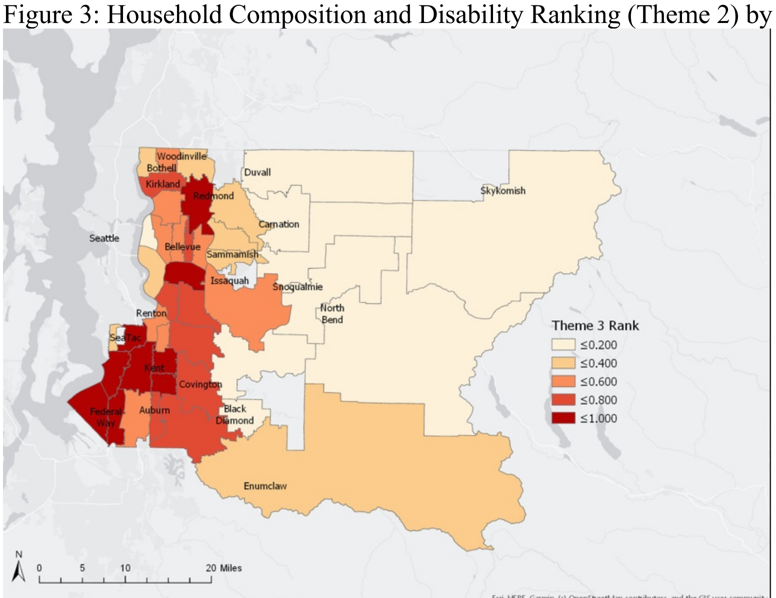

Figure 4: Minority Status and Language Ranking (Theme 3) by Zip Code in King County, WA

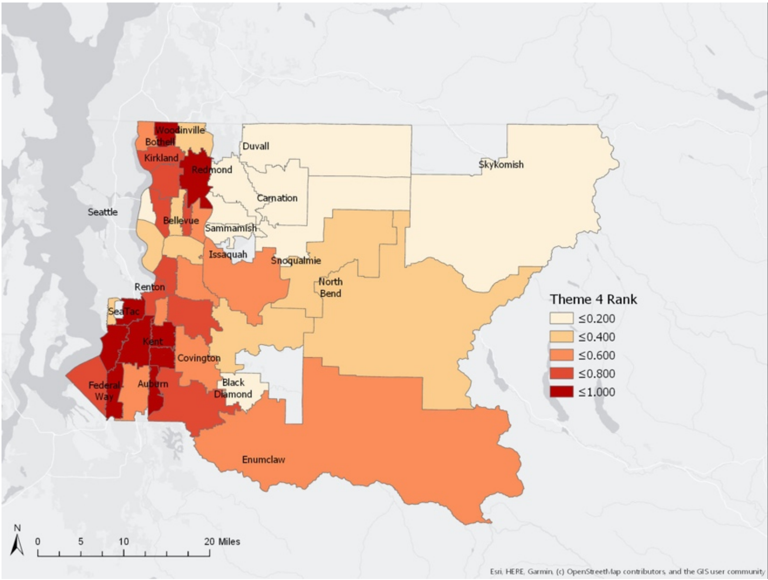

Figure 5: Housing and Transportation Ranking (Theme 4) by Zip Code in King County, WA

When the rankings for all four themes are summed together to produce a single composite measure of SVI at the zip code level, vulnerability looks quite similar to the trends observed at the theme level (Figure 6). Southern King County - Auburn, Federal Way, and Kent - are most socially vulnerable, with pockets of high vulnerability near Kirkland and Redmond. Zip codes of low social vulnerability are located near Duvall, Carnation, and Snoqualmie.

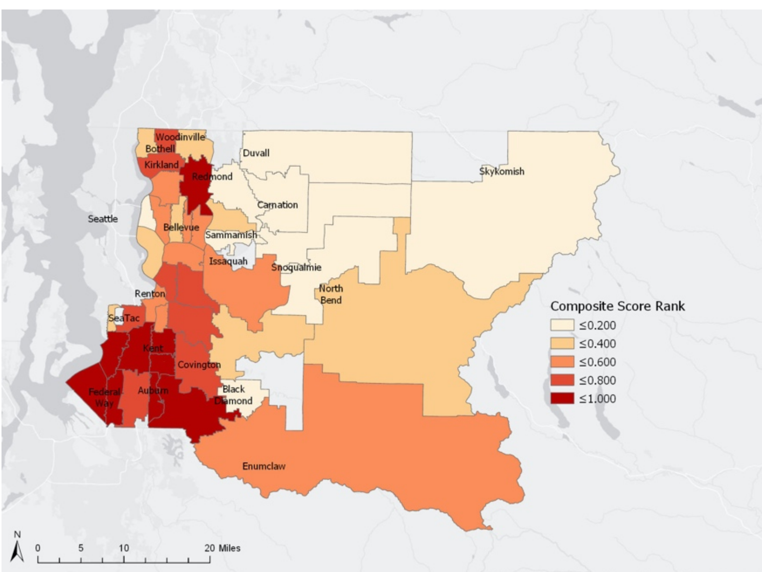

Figure 6: Composite Theme Ranking by Zip Code in King County, WA

4.2 Global OLS Models

Table 2 specifies the OLS equations and Table 3 reports the overall results of the global OLS linear regression models for each of the three SVI models. Model 1 performs the best with an adjusted R^2 of 0.365. Models 2 and 3 do not perform as well with an adjusted R^2 of 0.178 and

0.003 respectively. In all models, Pearson's r indicates a positive relationship between COMs and SVI. Model 1 and 2 are both statistically significant at $p < 0.05$ while Model 3 is not statistically significant. This indicates that an increase in data resolution also increases model performance. Model 1, which incorporates 15 SVI independent variables, demonstrates a significantly stronger predictive capability than Model 3, which only uses a single SVI composite score as the independent variable.

OLS Regression Equations	
Model 1	$COMs = 6.574 - 0.236(BelowPoverty) + 0.600(Unemployed) - 0.161(Income) + 2.464(NoHSD) + 1.011(Age65Over) + 1.795(Age17Younger) - 2.439(Disability) - 1.134(SingleParentHouse) - 0.783(Minority) - 0.713(EnglishLTW) - 0.027(MultiUnit) + 0.323(MobileHome) - 0.932(Crowding) + 1.176(NoVehicle) - 0.186(GroupQuater) + 0.362$
Model 2	$COMs = 6.906 - 0.560(Theme1) + 1.563(Theme2) - 1.026(Theme3) + 0.129(Theme4) + 0.412$
Model 3	$COMs = 6.921 + 0.078(CompositeScore) + 0.459$

Table 2: Ordinary Least Squares Regression Equations

Global OLS Model Results			
	Model 1	**Model 2**	**Model 3**
Pearson's r	0.769	0.506	0.050
R^2	0.592	0.256	0.003
Adjusted R^2	0.365	0.178	-0.022
Std. Error of Estimates	0.363	0.412	0.460
f-value, p-value	2.607, 0.015*	3.273, 0.021*	0.104, 0.748

Table 3: Ordinary Least Squares Regression Model Results (*statistically significant at $p < 0.05$).

Table 4 reports the standardized coefficient estimates for the three OLS regression models. Coefficient estimates represent the change in the dependent variables for every unit of change in the independent variable. In Model 1 (Table 4), the most significant independent variables explaining COMs are the number of individuals aged 17 year or younger ($t = 2.722$) and the number of individuals with no high school diploma ($t = 2.215$). Both variables are statistically significant ($p < 0.05$) and positively correlated. Within Model 1, no other independent variables are statistically significant in explaining COMs. Other independent variables captured in this model with a positive relationship include the number of individuals unemployed, aged 65 years or older, mobile home units, and without vehicles. The majority of independent variables, however, exhibit a negative relationship to COMs. The number of disabled individuals (t = -1.940) shows the strongest negative association with COMs although it is not statistically significant.

Within Model 2 (Table 4), Theme 2 (Household Composition & Disability) exhibits the most significant positive association to COMs (t = 3.524, $p < 0.05$). Theme 3 (Minority Status & Language) exhibits a strong negative association (t = -2.012) to COMs but is not statistically significant. Theme 1 has a weak negative associate while Theme 4 has a weak positive association with COMs. Within Model 3 (Table 4), the independent variable - composite SVI score - has a weak positive association that is not statistically significant.

Model Coefficients[a]				
	Variable	Standardized Coefficients	t	Sig.
Model 1	(Constant)		27.754	.000
	Below Poverty	-.152	-.177	.861
	Unemployed	.386	.695	.493
	Income	-.104	-.341	.736
	No High School Diploma	1.583	2.215	.035
	Aged 65 or Older	.649	1.737	.094
	Aged 17 or Younger	1.153	2.722	.011
	Disability	-1.567	-1.940	.063
	Single-Parent Household	-.729	-1.243	.225
	Minority	-.503	-.711	.483
	Speaks English Less than Well	-.458	-.575	.570
	Multi-Unit Structures	-.017	-.029	.977
	Mobile Homes	.208	.943	.354
	Crowding	-.599	-1.298	.205
	No Vehicle	.756	1.088	.286
	Group Quarters	-.120	-.439	.664
Model 2	(Constant)		51.401	.000
	Theme 1: Socio-economic Status	-.360	-1.120	.270
	Theme 2: Household Composition & Disability	1.004	3.524	.001
	Theme 3: Minority Status & Language	-.659	-2.012	.051
	Theme 4: Housing & Transportation	.083	.258	.798
Model 3	(Constant)		48.542	.000
	Composite Score	.050	.323	.748
	a. Dependent Variable: Customer Outage Minutes			

Table 4: Model 1, 2, and 3 coefficients

The OLS residuals are mapped in Figures 7-9 to examine how well each of the SVI models predicts COMs at the zip code level across King County. The blue color depicts zip codes where the predicted values are higher than observed COMs values (overprediction). The red color depicts zip codes where the predicted values are lower than observed COMs values (underprediction). The residual spatial patterns illustrate that predictive capability is better in certain zip codes, namely the zip codes near SeaTac and Mercer Island. All three models underpredict COM values in the zip codes surrounding Duvall, Enumclaw, Bellevue and Bothell. Overpredictions are associated with the zip codes surrounding Carnation, North Bend, and Snoqualmie. Further inspection of the maps also indicates increasing clustering of over and under predictions as the SVI models decrease in data resolution (i.e. moving from Model 1 to Model 3). These results are confirmed by the spatial autocorrelation statistics, as is shortly discussed, and suggests that model performance decreases as data resolution decreases.

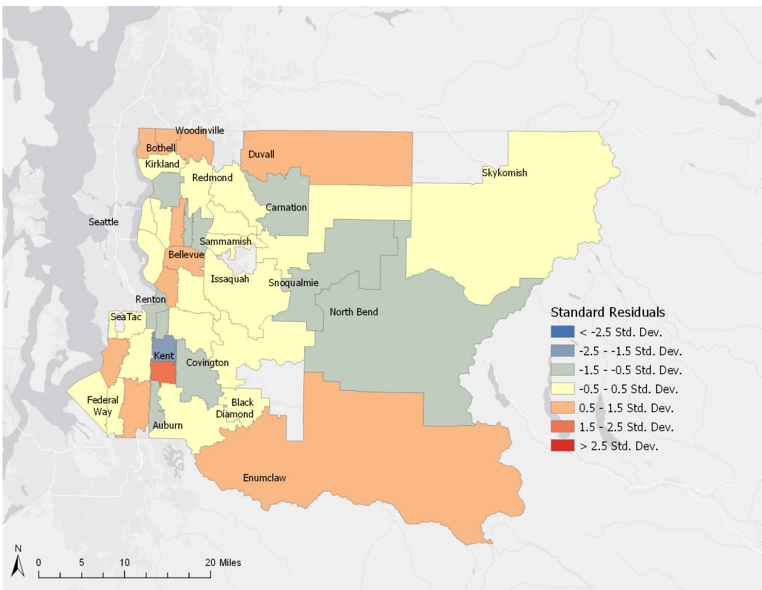

Figure 7: Model 1 standard residuals by Zip Code in King County, WA

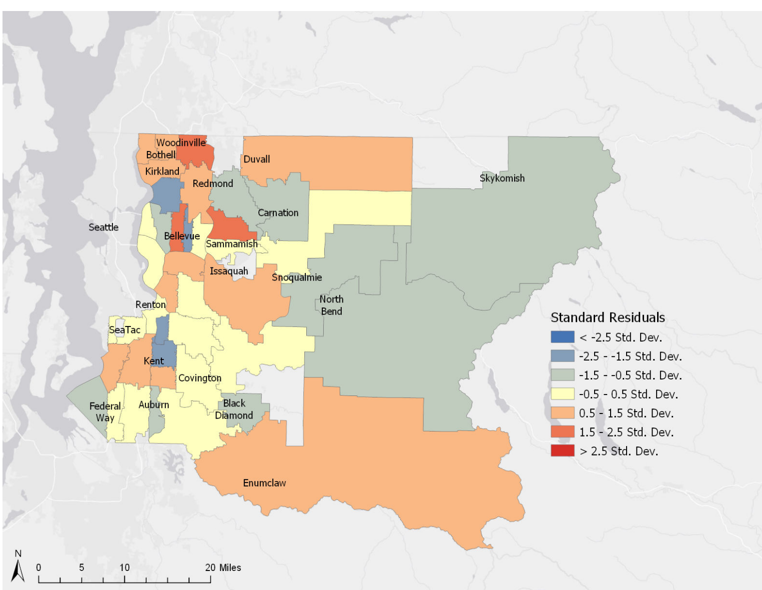

Figure 8: Model 2 standard residuals by Zip Code in King County, WA

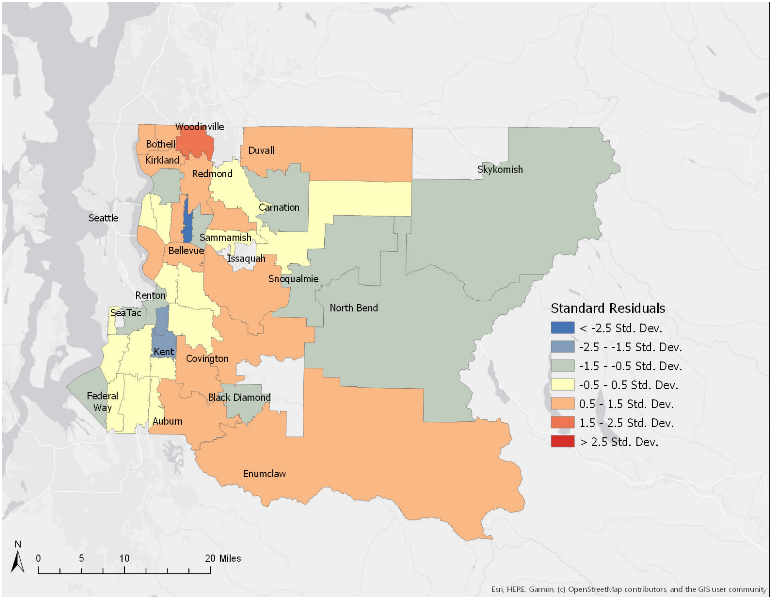

Figure 9: Model 3 standard residuals by Zip Code in King County, WA

In addition to the fit of the three SVI models, OLS diagnostic parameters are also examined (Table 5). First, stationarity is assessed using the Koenker (BP) Statistic. It determines if the relationships modeled are consistent in geographic space (stationarity) and data space (homoscedasticity). In all three models, the Koenker (BP) Statistic is not statistically significant. This indicates that the relationships between the SVI variables and COMs is consistent in that spatial processes represented in the models behave the same throughout King County and the data values are scattered to the same extent. Therefore, the global OLS models are deemed sufficient and a geographically weighted regression (GWR) is not necessary. Second, model bias is assessed using the Jarque-Bera Statistic which evaluates whether or not the residuals are normally distributed. In all three models, the Jarque-Bera Statistic is not statistically significant, indicating that the model predictions are not biased and OLS results are trustworthy. Lastly, residual spatial autocorrelation is assessed by running the Spatial Autocorrelation (Global Moran's I) tool in ArcGIS Desktop. This analysis assesses if the regression residuals are spatially random. Models 1 and 2 do not exhibit spatial autocorrelation and, therefore, the global OLS results are trustworthy. Model 3, however, does exhibit spatial autocorrelation ($p < 0.05$). This indicates that the clustering of residuals is unlikely a result of random chance and, therefore, key independent variables are missing from the model.

OLS Diagnostic Parameters				
Parameter		Model 1	Model 2	Model 3
Koenker (BP) Statistic	Value	18.662	2.966	0.023
	P-value	0.229	0.563	0.880
Jarque-Bera Statistic	Value	0.653	1.365	1.923
	P-value	0.721	0.505	0.382
Moran I's (spatialautocorrelation)	Value	-0.064	0.049	0.057
	P-value	0.275	0.494	0.028*

Table 5: OLS Diagnostic parameters for Models 1, 2, and 3 (*statistically significant at $p < 0.05$)

5. Discussion

The detailed analysis of electric power systems in relation to community characteristics, such as social vulnerability, is critical for disaster management planning and response. The results of this study demonstrate that there is a positive relationship between electric power outages and certain variables associated with social vulnerability. Overall, the results indicate that power outages are disproportionately occurring in areas that are more socially vulnerable in the PSE service territory in King County, WA. Furthermore, the results identify specific zip codes in which there is increased social vulnerability and power outages. This research will help disaster management practitioners plan and respond to unforeseen natural hazards, such as extreme weather events, that ultimately cause the majority of power outages. This in turn will decrease social vulnerability and increase the overall resilience of communities. The analytical model developed in this study has two primary findings useful for future disaster management activities.

The first finding of the study, as presented in Figures 1-6, shows that spatial distribution of power outages and social vulnerability substantially varies at the zip code level across PSE service territory in King County, WA. Power outages disproportionately occur with greater frequency and magnitude in the areas surrounding Bothell and Woodinville in northern King County. The most socially vulnerable communities are located in southern King County - Auburn, Federal Way, and Kent - with pockets of high vulnerability near Kirkland and Redmond. This generally indicates that differing levels of resources are required to restore power outages and mitigate impacts on socially vulnerable communities throughout the study area.

The second finding of the study demonstrates that there is a relationship between social vulnerability and electric power outages within PSE service territory in King County, WA. The social vulnerability index (SVI) is able to predict customer outage minutes (COMs) at a statistically significant level. For the statistically significant models - Model 1 and 2 - the relationship between COMs and SVI is positively correlated. As social vulnerability increases so does the magnitude of electric power outages. Models 1 and 2 can explain respectively 36.5% and 17.8% of the variation in COMs. As the level of SVI data resolution decreases in Model 3, however, the relationship between COMs and SVI is no longer significant. Thus Models 1 and 2 are able to best capture key variables that influence COMs. Importantly, the relationships in all three models exhibit spatial stationarity. The spatial processes between COMs and SVI behave the same throughout King County. This reflects reliability of the global OLS models. This study also finds that using a single SVI composite score - Model 3 - may be misleading when examining the influence on power outages. A higher level of data resolution, as demonstrated in Models 1 and 2, allows for a more accurate analysis of explanatory variables.

Among the fifteen census variables in Model 1, the most significant variables that explain COMs are the number of individuals aged 17 years or younger and the number of individuals with no high school diploma. Among the four SVI themes in Model 2, Theme 2 (Household Composition & Disability) exhibits the most significant positive association to COMs. This theme is composed of the following census variables: aged 65 or older, aged 17 or younger, civilians with a disability, and single-parent households. The reason why these variables are associated with increased power outages is not readily apparent.

The variables may represent communities with aging infrastructure and/or a lack of electric power restoration resources. The fragility of infrastructure, such as overhead distribution lines, is known to increase with age. Fragile infrastructure is more easily damaged, which causes increased power outages (Hosseini, Barker, and Ramirez-Marquez 2016; Dunn et al. 2018). Research also shows that electric utility companies prioritize service maintenance and restoration to areas with critical customers (i.e. hospitals and communication towers). It is uncertain if these conclusions apply to the dataset used in this study (Maliszewski and Perrings 2012). Social vulnerability and power systems are highly complex and dynamic processes, causal relationships are often changing and, in some cases, may remain hidden (Enarson 2007). A confluence of socio-economic and physical factors, many of which are not captured in this study, is a possible explanation. This requires a more detailed spatial analysis of SVI in relationship to electric power infrastructure, such as substations and distribution lines. It is important to note that this study does not address causality. Nonetheless, this study does reveal a positive association between power outages and social vulnerability.

6. Conclusion

To the author's knowledge, this is the first study to examine the relationship between power outages and social vulnerability. As such, this study has synthesized concepts and methods from multiple disciplines in order to present novel research with a practical application. Specifically, the results of this study can help disaster management practitioners identify locations of increased outages and socially vulnerable communities as well as identify specific social factors that increase the likelihood of power outages within communities across King County. In addition, this study also helps other researchers examine key variables in the casual relationship between power outages and social vulnerability in greater detail. Ultimately, this could reduce the impacts of power outages within communities that are already socially vulnerable.

The predictive capability of the models presented in this study suggests that further research is appropriate to analyze the relationship between power outages and social vulnerability. Firstly, future research should 1) model SVI against other power outage datasets and 2) model other social vulnerability indices, such as SoVI, against the PSE dataset to examine validity. Secondly, research is needed to examine why outages are occurring with more significant frequency and greater magnitude within these areas. To address causality, research should analyze the vulnerability of physical electric power infrastructure - based on type, age, and vegetation abundance - to weather events. Lastly, future research should also examine the specific impacts of power outages on socially vulnerable communities to understand if they are at an increased risk of disruption to health, sanitation, or water services. This certainly suggests a larger discussion concerning energy equity and resource allocation during natural and anthropogenic disasters.

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Chapter Five

Conclusion

The three studies presented in this dissertation demonstrate that resilience is a complex and multidimensional concept. There is not only a lack consistent measurement models but also confusion surrounding fundamental principles associated with resilience. This limits the applicability of resilience for electric power systems planning and management and, ultimately, hinders the development of standardized resilience practices. A systematic framework for measuring the resilience of energy system is important if critical infrastructure and communities are to absorb, adapt, and recover from disruptions by natural hazards, such as hurricanes and earthquakes. Motivated by those observations from literature synthesis, this dissertation offers a critical and consistent approach across theoretical and empirical perspectives. Using empirical data from King County, WA, this dissertation shows that the functional performance of electric power systems varies geographically across the Puget Sound Energy service territory. There are statistically significant clusters of both high and low magnitude power outage events. Furthermore, these outage events are significantly associated with certain aspects of increased social vulnerability, including the age of household members. This indicates that utility customers in the study area inequitably incur the costs of service disruptions.

The Resilience Measure Framework developed in Chapter 2 can help energy system practitioners, including policy makers and utility system operators, to design, implement, and monitor critical infrastructure and services. The measurement framework can also help navigate diverse stakeholder interests by identifying appropriate resilience principles, functional performance models, and strategies for the given decision situation. The empirical research presented in Chapters 3 and 4 demonstrates the application of quantitative methodologies to model functional performance, a key component of resilience. The heterogeneity in the functional performance, in both space and time, of the PSE electric grid as well as the level of association with social vulnerability indicates that this is a worthwhile line of inquiry that requires further research. Specifically, future research should examine why functional performance is degraded in certain areas and if this lack of functional performance increases the vulnerability and, thereby, decreases the resilience of communities to natural hazards. Such assessment models, however, require higher resolution data about electric grid infrastructure, performance, long-term targets.

It is important for power system planners, decision makers, and other practitioners to understand how the resilience of an energy systems can impact communities. This can facilitate a place-based disaster management planning approach by determining areas where power outages are causing increased harm to communities and, hopefully, allocating the necessary resources to mitigate such harm. Ultimately, resilient energy systems will strengthen the capacity of communities to absorb, adapt, and recover from natural hazards.