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TRADEOFFS IN POWER GRID OPERATION DURING A PUBLIC SAFETY POWER SHUTOFF

by

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December 2020

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TRADEOFFS IN POWER GRID OPERATION DURING A PUBLIC SAFETY POWER SHUTOFF

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ABSTRACT

This thesis considers challenges associated with managing the risk of wildfires caused by electric utilities, specifically the use of deliberate, and potentially widespread, power outages termed Public Safety Power Shutoff (PSPS) events. A PSPS event is a way to reduce potential liability in utility-associated wildfires, but it also creates additional dangers and economic hardships for utility customers. This thesis performs three modeling and analysis tasks: (1) it presents an extensive exploratory data analysis on the Pacific Gas & Electric (PG&E) power grid, utility-caused ignitions, and past PSPS events; (2) it develops models to gain insight on the PG&E decision process during PSPS events; and (3) using power outage studies and economic models, it estimates the social cost of PSPS events.

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List of Acronyms and Abbreviations

AIC Akaike information criterion

BIC Bayesian information criterion

CAISO California Independent System Operator

CAL FIRE California Department of Forestry and Fire Protection

Cal OES California Governor's Office of Emergency Services

CPUC California Public Utilities Commission

DC direct current

DOD Department of Defense

EOC Emergency Operations Center

FIA Fire Index Area

FPI Fire Potential Index

GIS Geographic Information System

GLM Generalized Linear Model

HFTD High Fire Threat District

kW Kilowatt

kWh Kilowatt-hour

MILP mixed-integer linear program

MW megawatt

NIFC National Interagency Fire Center

NPS Naval Postgraduate School

NWS National Weather Service

OPS Optimized Power Shutoff

PG&E Pacific Gas & Electric

PSPS Public Safety Power Shutoff

ROC receiver operating characteristic

RF Random Forest

RFW Red Flag Warning

SOC Safety Operations Center

USG United States government

USN U.S. Navy

WMP Wildfire Mitigation Plan

WUI Wildland Urban Interface

Executive Summary

Wildfires have become an increasing concern in the Western United States over the last decade, particularly in California. Years of forest mismanagement, build-up of dry fuels, and climate change have created conditions ripe for wildfires, sparked naturally or otherwise.

In 2017 and 2018, there were four catastrophic wildfires in Northern California caused by electric utility operations. These fires have been ranked among the top-20 deadliest wildfires in the history of California. Utility companies found responsible for the fires faced lawsuits and bankruptcy, and an increased awareness around utility-caused wildfires led to changes in regulations and legislation.

As a result of these and other incidents, utility companies are keenly focused on ways of mitigating the risk and liability of their operations. During periods of extreme risk, electric utilities have additionally started to stage widespread power outages—termed Public Safety Power Shutoff (PSPS) events—in an effort to reduce the risk of wildfires. The purpose of this thesis is to identify and examine tradeoffs in the timing, scope, and duration of PSPS events.

This thesis performs three modeling and analysis tasks: (1) we conduct an extensive exploratory data analysis on the Pacific Gas & Electric (PG&E) power grid, utility-caused ignitions, and past PSPS events; (2) we develop models to gain insight on the PG&E decision process during PSPS events; and (3) using power outage studies and economic models, we estimate the social cost of PSPS events.

To achieve these objectives, this thesis curates, integrates, and visualizes data from a wide variety of sources, including PG&E, the California Public Utilities Commission, and the California Independent System Operator. This allows us to identify interactions between the electric power grid, terrain, climate, and wildfire risk. We learn that ignition risk varies widely across the power grid, and that utility-caused ignitions are common and have the potential to grow into large fires. Additionally, PSPS events can vary largely in scope based on duration, the number of customers affected, and the lost electric load. Much of the data we use is part of a yearly effort put out by PG&E in their Wildlife Mitigation Plan; new data will be available in 2021 that may supplement this analysis and provide more information

on the state of the power grid.

Furthermore, we develop simple regression models to determine important factors in PG&E's decision-making process when executing PSPS events. We observe the key drivers to be whether or not a circuit crosses the High Fire Threat District (and what proportion of it is within this area) and a PG&E-calculated risk score. Future work would benefit from having more complete and detailed data for all assets in the power grid to conduct a more thorough analysis.

Finally, we translate concrete impact measures such as the duration, customers, and lost load during a power shutoff into the overall social cost of PSPS events. We determine that for past events, this value ranges from tens of millions to potentially billions of dollars. We estimate a lower bound for this cost that does not consider the varying electric demand of commercial and/or industrial customers or customers PG&E classifies as "other" or "medical baseline".

The next phase in this research should consider a higher level of fidelity in modeling wildfires, the electric power grid, and the costs of power outages. This would entail formulating an optimization problem that explores tradeoffs in the timing, scope, and duration of PSPS events.

Finally, the results from analyses in this and related studies have implications for Department of Defense (DOD) operations. Some military installations in the U.S. are exposed to wildfire risk, and all are vulnerable to power outages. The DOD would greatly benefit from better understanding the interactions between wildfires and the electric power grid, as well as how to restore power safely and efficiently.

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CHAPTER 1:
Introduction

Wildfires have become an increasing concern in the Western United States over the last decade, particularly in California. Years of forest mismanagement, the build-up of dry fuels, and climate change have created conditions ripe for wildfires, sparked naturally or otherwise. This has coincided with increased development at the Wildland Urban Interface (WUI), defined by the Forest Service as "any area where humans and their development meet or intermix with wildland fuel" (Stein et al. 2013). The fire risk is heightened during the dry and windy conditions characteristic of the California wildfire season.

In 2017 and 2018, there were four catastrophic wildfires in Northern California caused by electric utility operations. These fires — the Camp Fire, Tubbs Fire, Redwood Valley Fire, and Atlas Fire —- have been ranked among the top-20 deadliest wildfires in the history of California (CAL FIRE 2019). Utility companies found responsible for the fires faced lawsuits and bankruptcy, and an increased awareness around utility-caused wildfires led to changes in regulations and legislation (Pacific Gas & Electric Company 2020b).

As a result of these and other incidents, utility companies are keenly focused on ways of mitigating the risk and liability of their operations. Many of these mitigation strategies focus on vegetation management and system hardening. Tree trimming and dead tree removal are common practices that keep the space around high-voltage lines free of vegetation or falling debris that could spark an ignition. Utility companies regularly inspect equipment to perform any maintenance, repairs, or replacement of damaged or outdated equipment.

During periods of extreme risk, electric utilities have additionally started to stage widespread power outages in service territories in an effort to reduce the risk of wildfires. One of these utility companies, Pacific Gas & Electric (PG&E), held eight of these outages, termed Public Safety Power Shutoff (PSPS) events, in 2019 alone (Pacific Gas & Electric Company 2020e). Although power shutoffs such as these had been carried out in the state before, none previously had been executed at such a large scale. Caught between the danger of devastating wildfires and the additional dangers and economic hardships that come with power shutoffs, the public is outraged. Despite this, periodic utility-driven power outages are expected to continue occurring for the foreseeable future.

1.1 Tensions in PSPS Events

Thousands of miles of overhead power lines run through wildland areas, and even the smallest spark from utility equipment could ignite what develops into a massive fire. De-energizing power lines, via execution of a PSPS event, could mean saving thousands of wildland and urban acres from burning, and therefore, saving lives of California residents. However, carrying out a PSPS event also has a negative effect on the activities and operations of homes, businesses, schools, healthcare facilities, and emergency responders. These shutoffs create a myriad of dangers to the public, including disruptions in communication and transportation. Because a widespread power outage is itself an emergency, PSPS events are a test in emergency preparedness for communities at large.

For PG&E, a PSPS event is a way to reduce their liability in utility-associated wildfires. The equipment used in the power grid requires regular maintenance, and in many cases, upgrades to outdated systems. There is no question that failures are inherent to the grid. Even with a sizable workforce, it has proven to be almost impossible to identify all hazards and failures in the grid, especially when high-wind events occur as often as they do. Because of this, a PSPS event may be the only sure way of reducing fire risk in some situations.

Another feature of the power grid that has become evident as a result of PSPS events is the limited control structure. In most cases, controls for turning off power are not available at the city-level, or even country-level. Rather, they are available for an entire region, which is delimited by one or multiple interconnected power sources. Therefore, many regions could be affected by a power outage due to a single high fire risk area.

A rework of the power grid will certainly be necessary in the future, but it is not a solution to the very immediate wildfire threat California will experience in the coming years (Pacific Gas & Electric Company 2020a). In the short-term, PSPS events will continue to occur and will likely become more frequent. An effective and safe decision policy needs to be developed to answer the following questions.

1. Under what conditions should the power be shut down?
2. Where should the power be shut down and for how long?

3. When and how should the power be restored?

However, there is considerable work to do before such a prescriptive decision model can be developed.

1.2 Thesis Goals

The purpose of this thesis is to identify and examine tradeoffs in the timing, scope, and duration of PSPS events. We conduct an exploratory data analysis to develop a descriptive model of utility-caused wildfires and associated PSPS events. We then use our understanding of these tradeoffs to build predictive models of PSPS events and their effects. Greater understanding of both aspects can help improve the system to the benefit of both customers and utility companies.

The remainder of this thesis is structured as follows. Chapter 2 provides background on PSPS events and utility operations. This chapter also reviews related literature on fire-spread, electric power operation, and risk mitigation. Chapter 3 introduces multiple data sources and conducts an exploratory data analysis. We conduct a regression analysis in Chapter 4 to gain insight on tradeoffs. Finally, Chapter 5 concludes the work and offers recommendations for future studies.

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CHAPTER 2: Background

The prominent wildfire risk present in California today has developed over many years. Natural processes have shaped the landscape, and the actions of utility companies, government agencies, and individuals over the past decade have set the foundation for the problems we see today. There are four general scenarios in which electric utility equipment can cause wildfire ignitions (Figure 2.1). Ignitions are commonly caused by failures or disruptions on power lines or poles that are associated with strong winds or vegetation.

One of the primary responses to wildfire risk conducted by utility companies is vegetation management. PG&E follows regulations set by the California Public Utilities Commission (CPUC) in General Order No. 95 (California Public Utilities Commission 2018). This ruling requires “clearances of 4 feet around power lines in high fire-threat areas with recommended minimum clearances of 12 feet or more at time of prune to ensure compliance year-round”, which is shown in Figure 2.2 (California Public Utilities Commission 2018). Maintaining these standards requires routine maintenance around power lines, and it does not fully protect against vegetation pushed into lines or falling debris during strong wind events. For this reason, utility companies consider de-energizing power lines.

In this chapter we provide background information on PSPS events, utility operations, and previous research pertinent to this thesis.

2.1 Public Safety Power Shutoffs

This section describes the events leading up to, during, and after a PSPS event. It also examines a past example of a power shutdown and the stakeholders involved.

2.1.1 Description of Event

PG&E describes a PSPS event as the need to turn off electricity to an area, in the interest of community safety, when certain environmental conditions are forecasted (Pacific Gas & Electric Company 2020e). These conditions could include high-speed, gusty winds, low humidity levels, and an elevated risk of fire (Pacific Gas & Electric Company 2020e). The

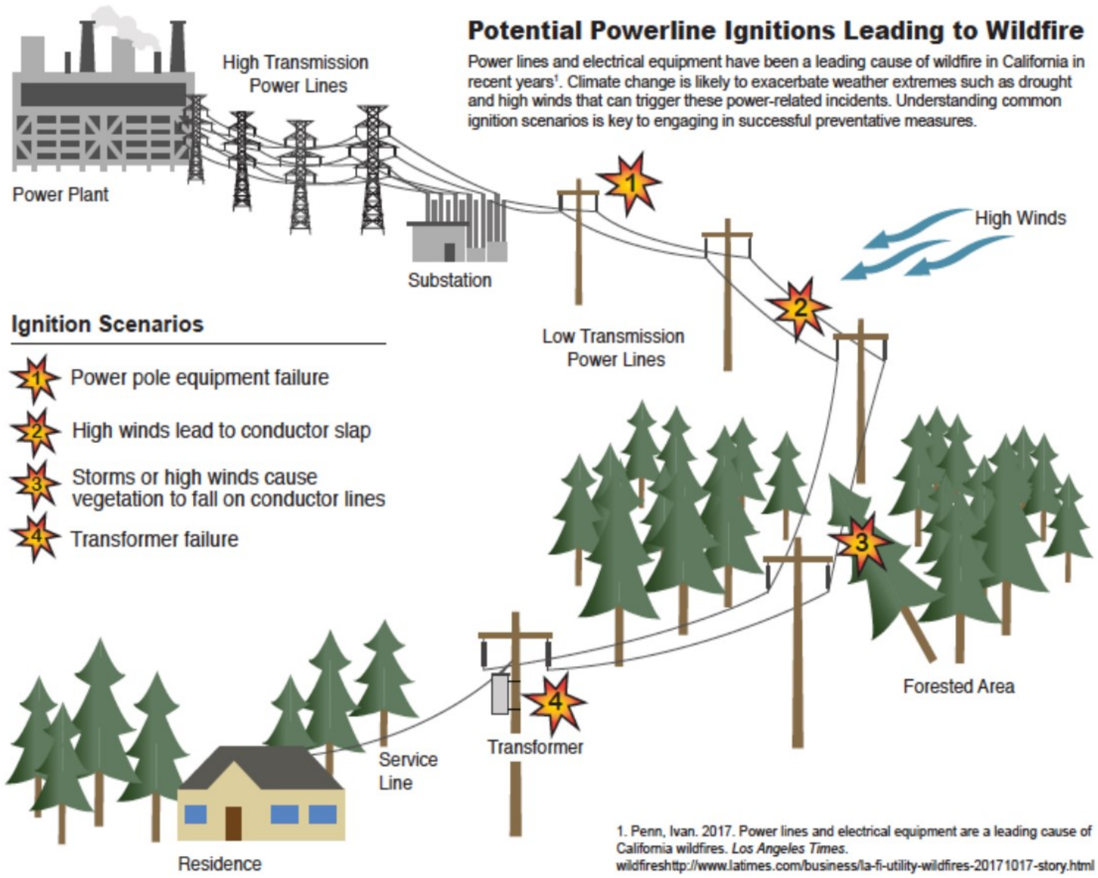

Figure 2.1. Power Line Ignition Scenarios. Source: Karuk Tribe Department of Natural Resources (2018).

purpose of a PSPS event is to de-energize the portion(s) of the power grid subject to these conditions in order to mitigate the risk of wildfires potentially ignited (or intensified) by utility operations. A single PSPS event could leave nearly one million customers without electric power, spread across several cities and counties (Pacific Gas & Electric Company 2020a). Thus, the execution of a PSPS event requires decision-makers to consider not only when and where to shut the power off, but also how to keep the affected community informed.

PG&E does not have a set schedule for power shutdowns, as the criteria for them are "dynamic and naturally unpredictable" (Pacific Gas & Electric Company 2020e). In the recent past, the shutdowns were executed several times a year (roughly three to eight

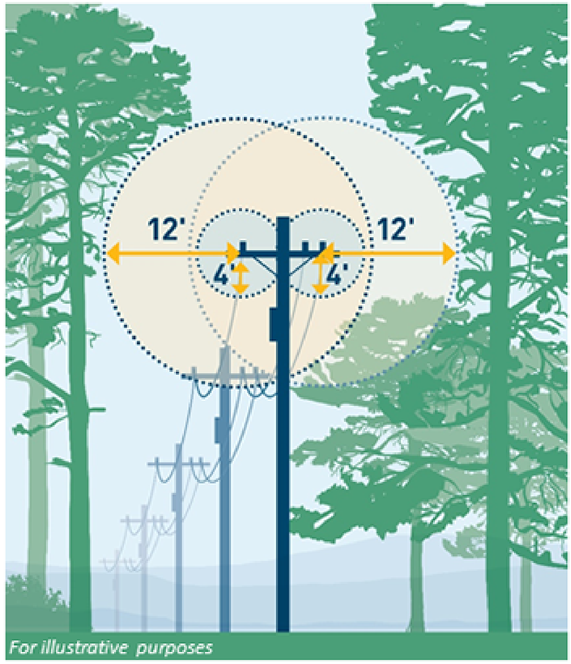

Figure 2.2. Regulations for Vegetation Management. Source: Pacific Gas & Electric Company (2020g).

events), during the California fire season from late spring to early fall (Pacific Gas & Electric Company 2020e). As a result, PG&E monitors current and upcoming weather conditions, as well as terrain and forest conditions, year-round in an effort to identify potential wildfire hazards.

However, there are (at least) three distinctly different processes involved in PSPS events, each of which evolves over different timescales: natural processes involving the wilderness itself, human processes involved with development and forest management, and utility processes involved in the operation of the grid (see Figure 2.3). These parallel processes include events that occur years, months, and days before a PSPS event.

A utility company begins to consider the possibility of a PSPS event once forecasted conditions indicate a high-likelihood of wildfire. More specifically, PG&E operates at five different levels of PSPS potential (Pacific Gas & Electric Company 2020d).

1. "Not expected": conditions that would warrant a PSPS event are not expected in the next seven days.

2. “Elevated”: the upcoming weather conditions (within seven days) are being monitored for elevated risk.
3. “PSPS Watch”: the possibility of a PSPS event in upcoming days is likely. PG&E’s Emergency Operations Center (EOC) activates and prepares to carry out the event. This level of operation is typically issued 72 hours in advance of an expected PSPS.
4. “PSPS Warning”: the EOC is active and customers residing in the affected area are notified. Although this level of operation suggests that a PSPS event is very likely, it does not guarantee it.
5. "Weather All Clear": the severe weather event has passed and it is safe for PG&E crews to begin the power restoration process.

The PSPS concludes when electric power has been restored to all affected regions of the electric power grid (Pacific Gas & Electric Company 2020e). As indicated in the “PSPS Warning” level, none of these operating conditions guarantee that a PSPS event will or will not occur (Pacific Gas & Electric Company 2020d). Rapid and unexpected changes in the weather forecast could escalate or de-escalate conditions on an hourly basis.

In addition to deciding when a PSPS event will take place, PG&E decision-makers must also determine where it will take place. This means considering not only which transmission and/or distribution lines to de-energize, but also which customer regions will be left without power. Ideally, only the lines and customers in the high fire-risk areas would be impacted. However, due to the control structure of the electric power grid, a community that is not at risk may also experience a power shutdown (Pacific Gas & Electric Company 2020e). Power lines travel long distances across the state, and controls are present at different scales (whether that be at the city-level or regional). Rather, they are available for zones, which are delimited by one or multiple interconnected power sources (Pacific Gas & Electric Company 2020c). A PSPS event may extend far past the area where wildfire mitigation is necessary. This creates a tradeoff between wildfire prevention and impact on the public.

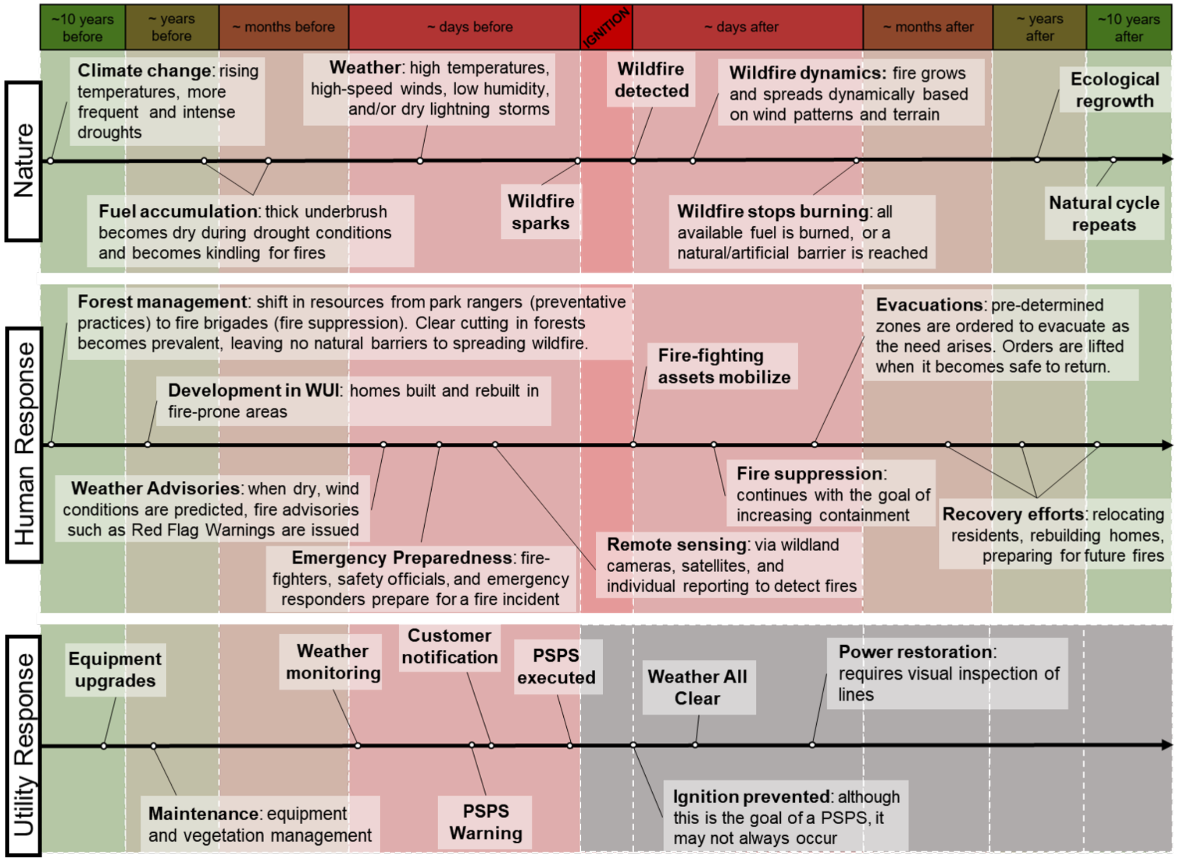

Figure 2.3. Wildfire Progression Timeline. There are three timelines – (1) Nature, (2) Human response, (3) Utility response – which occur in parallel and interact. The top timeline shows some of the events that create fire-prone forests, the actual ignition event, and the natural dynamics, recovery, and growth that occur afterwards. The middle timeline shows the steps taken by fire and emergency agencies to detect, respond to, and control wildfires. The bottom timeline highlights the sequence of events that occur during a PSPS.

One way to measure community impact is through the number of households, businesses, and healthcare facilities that report not having power during a PSPS event. Still, this tends to grossly underestimate the number of individuals affected. This is because PG&E measures customers based on customer accounts, but a single account can serve multiple individuals (Pacific Gas & Electric Company 2019c). Measuring the economic impact on the community is another alternative. Most businesses, including ones deemed “essential,” are not able to operate during a power shutdown. Businesses may stall the production and sales of goods, food in grocery stores may spoil, and waged workers may not be getting paid. These all manifest as economic losses for the community. Less tangible are the additional dangers the public must face as a result of power shutdowns. Large-scale power outages disrupt transportation and communication; this is the very same transportation needed for evacuations and communication required to report fire hazards and up-to-date information to residents in affected areas. An outage also decreases the readiness of health facilities and first responders, even when backup power generation is available. The community consequences could be minimal or much more adverse depending on how long the power is off.

A PSPS will last at least as long as the high-risk weather event, which may be unpredictable (Pacific Gas & Electric Company 2020e). The duration of the entire event is also determined by how long it takes to turn the power back on. Once the weather event has passed, the restoration process occurs, which has its own associated fire risks. PG&E ground and aerial crews must visually inspect power lines to identify any damage that could have occurred while lines were de-energized (Pacific Gas & Electric Company 2020e). Before these crews can restore power, damage to equipment and/or any other hazards found need to be addressed. The time it takes to restore power varies greatly, and is dependent on (1) the number and length of the lines that must be inspected, and (2) the aerial and ground resources available. In 2019, PG&E’s goal was to restore power to all de-energized circuits within 24 daylight-hours (Pacific Gas & Electric Company 2019b). Therefore, a PSPS could leave customers without electric power for multiple days— days when an immediate fire risk may not even be present. Although determining the duration of a PSPS event is part of the decision-making process, it is not totally within the control of the utility company.

A PSPS may reduce the risk of fire, but it also creates economic, social, and health hazards, which decision makers must consider.

2.1.2 Example PSPS event

This section reviews the timeline of events and decisions made for a past PSPS. The information here was derived from a report to the CPUC in Pacific Gas & Electric Company (2019c).

In November of 2019, PG&E held a PSPS event in an effort to reduce the wildfire risk in communities north of the San Francisco Bay Area. Strong winds, low humidity levels, and low moisture content in dead and live fuels created an elevated fire risk. The event began on November 20 at 06:20 when the first circuit was de-energized and ended on November 21 at 21:56 when the last circuit was restored, lasting approximately 39 hours (Pacific Gas & Electric Company 2019c).

Beginning a week earlier, PG&E weather models predicted gusty and high-speed winds in the regions as far west as the North Bay and as far east as the North Sierra (Figure 2.4). On November 15, PG&E set these regions to an "Elevated" status for a potential PSPS, and two days later, the EOC was fully operational and the status changed to a “PSPS Watch”. At this time, utility operators identified sections of the electric power grid that were at risk and needed to be de-energized. For distribution lines, PG&E determined which circuits would be affected and at what device level. For assets at the transmission level, risk was analyzed based on the structure conditions, past outage data, and the most recent inspection of equipment. On November 18 and 19, the National Weather Service (NWS) declared multiple Red Flag Warnings (RFWs) in the area, further verifying the forecasted weather patterns.

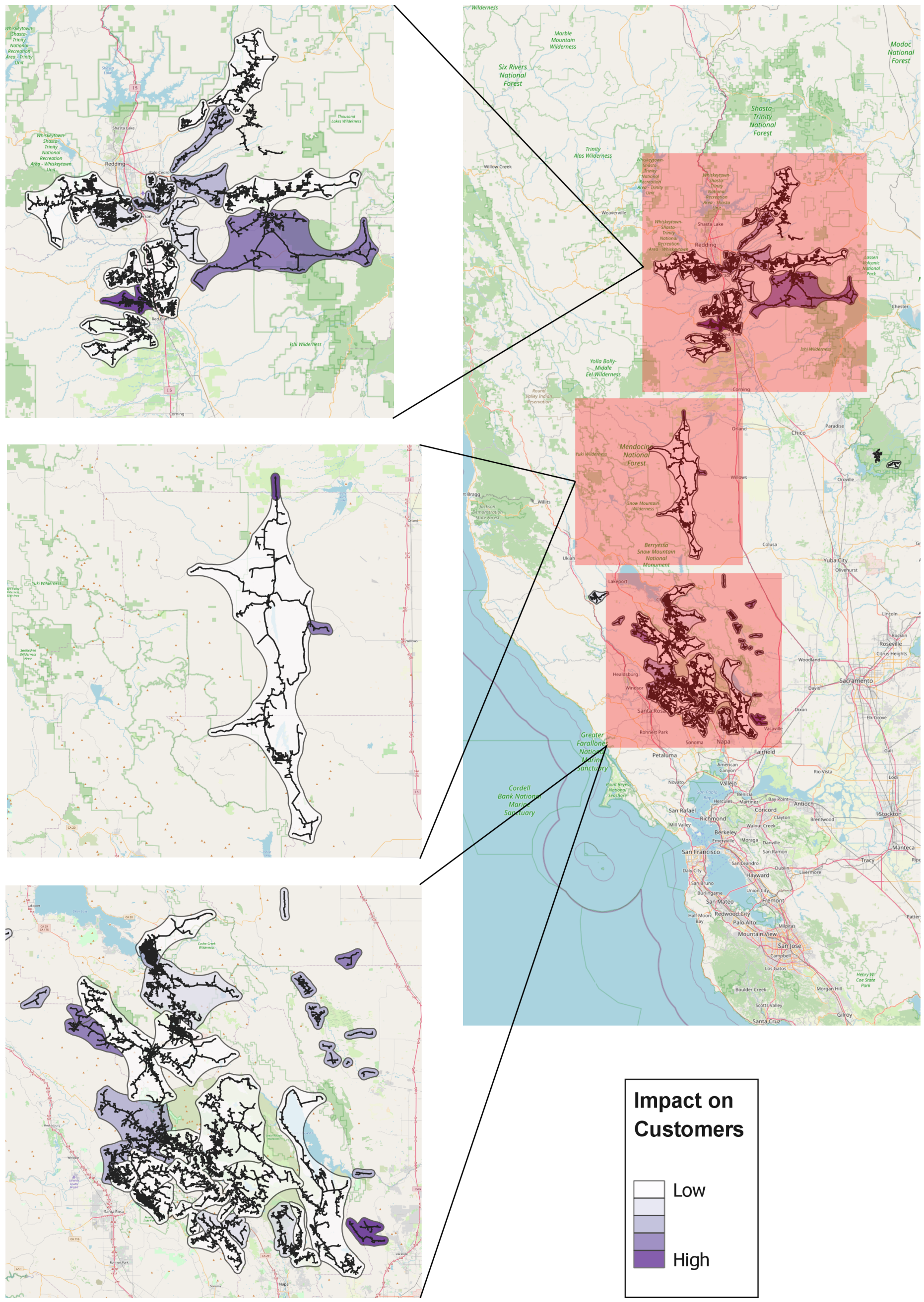

Figure 2.4. November 2019 Power Shutoff Areas. These maps show three of the affected regions in the PSPS event that occurred on November 20 and 21, 2019. The right panel shows an overview of the three Northern California regions, and the left panels provide a more detailed view. The purple-shading scale is a measure of the impact on residents, businesses, and facilities in the region, which is calculated as the total number of customer-hours without power. A darker shade means that more customers, more hours, or both were part of the PSPS event. Adapted from Pacific Gas & Electric Company (2020a).

As weather conditions continued to be monitored, PG&E actively engaged with customers in the potentially affected areas. Notifications occurred in three phases: (1) advanced notifications, (2) notifications during the shutdown, and (3) notifications once the power was restored in an area. The utility company sent over 49,900 direct notifications to customers via calls, text messaging, and e-mail (Pacific Gas & Electric Company 2019c). Social media and local news outlets were also used to raise awareness of the potential de-energization. Medical baseline customers, who have special energy needs due to medical conditions, were the focus of additional outreach efforts, including door-to-door contact when acknowledgement of other communication methods was not made.

With all customers notified and no change in the weather conditions, the final decision to de-energize the identified lines was made on the morning of November 20. It was not made, however, until all affected critical facilities, such as emergency responders, were confirmed to have some form of back-up power generation to continue operations (Pacific Gas & Electric Company 2019c). During the event, 49,202 distribution customers were de-energized across the region. Of these customers, 42,453 were classified as residential, 5,409 were classified as commercial or industrial, and of the total there were 2,432 medical baseline customers (Pacific Gas & Electric Company 2019c).

On the evening of November 20, PG&E issued the first "Weather All Clear" notification and began the power-restoration process. All affected lines were visually inspected to identify any damage or other hazards that could have occurred during the power shutdown. PG&E had pre-positioned and prepared field resources and helicopters to begin the inspections and power restoration immediately. For this event, 5,600 personnel and 45 helicopters were used, and 15 cases of damages and hazards needed to be repaired and cleared (Pacific Gas & Electric Company 2019c).

An after-action review was conducted on November 22, where internal and external feedback was collected from emergency response teams, the California Governor's Office of Emergency Services (Cal OES), and the California Department of Forestry and Fire Protection (CAL FIRE). Four of the key areas of improvement identified were: (1) enhanced scope ability and timing accuracy, (2) strengthening data quality, (3) improved estimation of restoration time, and (4) improved map precision.

2.1.3 Stakeholders and Perspectives

There are four entities heavily involved in the execution and impact of a PSPS event: (1) the utility company, (2) customers, (3) emergency responders, and (4) governmental agencies. All stakeholders want to maximize safety during a PSPS event and during the fire season. However, they all have different perspectives on how to best achieve these goals. Each stakeholder also has a different way of characterizing the risk associated with a PSPS.

Utility Companies

Utility companies are a primary stakeholder. They have the greatest responsibility and the greatest liability when it comes to the planning, execution, and consequences of a power shutoff. The mission of PG&E is "to safely and reliably deliver affordable and clean energy to our customers and communities every single day, while building the energy network of tomorrow" (Pacific Gas & Electric Company 2020f). With millions of customers spread across north and central California, providing reliable power in the face of growing wildfire risk is a challenging problem (Pacific Gas & Electric Company 2020f). In essence, PG&E must create a robust decision policy for power shutdowns that balances the tradeoffs between wildfire mitigation and community impact.

PG&E is facing multiple lawsuits and has filed for bankruptcy as a result of the role the company played in wildfires the past few years (Pacific Gas & Electric Company 2020b). On the other end of the spectrum, PG&E has also faced backlash for conducting PSPS events to avoid the catastrophic wildfires of the past. As a company, their main objective is to minimize liability. This breaks down into three smaller goals: (1) minimizing wildfire risk, (2) minimizing the number of customers without power, and (3) maintaining the perception of reliable electric power delivery. PG&E, as well as all other utility companies in the state, is regulated by the CPUC. One of the duties of the CPUC is to set operating constraints on utility companies, such as service standards and safety rules (California Public Utilities Commission 2020). These regulations may restrict decision-making for the utility company in regards to a PSPS. Additionally, equipment maintenance schedules, assets on private or protected land, and the inherent uncertainty of forecasting weather and fire conditions also limit utility operations. For utility companies, PG&E among others, the decision to turn off power is a tradeoff between wildfire safety and reliability in the eyes of the customer. This tradeoff has far-reaching consequences in the economic realm and for policies, both of which have immediate and long-term impacts.

Customers

Customers come in many forms. There are households with families, students, and essential workers. There are businesses ranging anywhere from a "Mom-and-Pop" shop to a commercial space housing global companies. Hospitals, doctors' offices, and emergency clinics also fall under this umbrella. Customers want reliable electric power provided at rates that reflect the quality of service. They also prioritize their well-being and the safety of their property and possessions; these could be put at risk during both a wildfire and a PSPS event. In terms of the provision of electric power, customers are limited by the controls afforded to them by the utility companies; this could mean devices like smart meters or back-up generators. Risk mitigation for customers comes in the form of disaster preparedness which can mitigate the dangers presented by wildfires and shutdowns. Compared to the utility companies, customers think about risks and consequences at a smaller geographic scale and a shorter time span.

Emergency Responders

Firefighters, police, state troopers, and paramedics play a key role in PSPS events. They are not only responsible for the protection and preservation of life, property, and the environment, but they also serve as liaisons between the public and utility companies and governmental agencies during PSPS events and wildfires. Their main objectives are to raise awareness about these emergencies and to manage people and resources during them. Like the utility companies, they are limited by the information available in environmental forecasts. First responders are typically thinking about risk at a regional level.

Government Agencies

There are three state and federal agencies which hold particularly high stakes in California regarding power shutdowns and wildfires: CAL FIRE, the U.S. Forest Service, and Cal OES. CAL FIRE is dedicated to the fire protection and conservation of the millions of acres of California's wildlands; this organization also provides varied emergency services to over half of the counties in the state (CAL FIRE 2020). The mission of the Forest Service is to maintain the health, diversity, and productivity of the country's forests (U.S. Forest Service

2020). In the state of California, much of the forest management relating to wildfire control and mitigation falls upon this organization. Cal OES is tasked with assuring the state's readiness to respond to and recover from disasters and hazards (Cal OES 2020). These three agencies communicate and work with each other, as well as with the other three stakeholders. The combined efforts of forestry management (on the part of Forest Service) and vegetation removal (on the part of utilities and CAL FIRE) prevents wildfires and PSPS events from occurring in heavily populated areas. By working together, local police departments and Cal OES, lead outreach programs to make sure California residents are informed about the environmental risks in their area, as well how to prepare for an emergency. Overall, these agencies are limited by funding and resources which determines how involved they are with the community.

2.2 Characterizing Wildfire Risk

Electric utility companies are constantly monitoring weather conditions to assess the wildfire risk. This involves several entities, including local meteorologists and weather services, as well as state and national agencies (Pacific Gas & Electric Company 2020e). PG&E considers multiple environmental factors, which could all warrant a PSPS event, but may not be sufficient on a case-by-case basis. The weather factors are: humidity levels, forecasted winds, and dry fuel conditions (Pacific Gas & Electric Company 2019c). A low humidity level, typically less than 20%, is an indicator of heightened wildfire risk (Pacific Gas & Electric Company 2019c). Sustained and gusty winds with speeds greater than 25 miles per hour could also elevate the fire risk (Pacific Gas & Electric Company 2019c); this risk is tightly coupled with temperature and terrain. High-speed winds also pose a threat to utility equipment; lines could become tangled, poles could be knocked over, and nearby foliage could come into contact with conductive materials. Additionally, fuel moisture content can indicate the fire potential in an area. Fuel moisture measures the amount of water present in dead and live organic material, expressed as a percentage of the dry weight of the type of fuel (NOAA 2020). For example, in the Los Padres National Forest, fuel moisture content may be measured from tree bark, canopy foliage, and debris on the forest floor. When fuel moisture content is low, fires can start easily and spread rapidly (NOAA 2020). Data on humidity, winds, and dry fuels is collected from local weather stations and by PG&E field crews (Pacific Gas & Electric Company 2019c).

Advisories and warnings issued by state and national agencies also play a major role in PG&E's decision process when executing a PSPS event. The NWS issues RFWs, which can lead to a PSPS event in conjunction with other conditions (Pacific Gas & Electric Company 2020e). These warnings indicate that high temperatures, very low humidity levels, and strong winds are predicted to combine, making wildfires very likely. The National Interagency Fire Center (NIFC) also designates critical burn areas and identifies high fire-risk days (Pacific Gas & Electric Company 2020e). These advisories, along with the climate data, are collected and evaluated at PG&E's wildfire Safety Operations Center (SOC), where it is decided whether a not a PSPS event is likely to occur within a one-week time frame (Pacific Gas & Electric Company 2020e).

During the planning of a PSPS event, regional maps also aid decision-makers. There are three maps in particular: (1) PG&E Geographic Zones map, (2) CPUC Fire Threat map, and (3) Fire Potential Index map. The first shows the boundaries of PG&E's service territory. The second designates areas with an elevated risk of fires due to electric power lines, and the third shows historical data on fire risk.

The PG&E Geographic Zones (Figure 2.5) map gives insight into the control structure of the power grid. It shows nine regions of PG&E's service territory which, to some degree, are interconnected by the lines that carry electricity (Pacific Gas & Electric Company 2020e). Customers within a zone are likely to experience similar weather and have similar terrain. Therefore, these zones can be interpreted as units where a PSPS event could occur and effect most customers within. It is important to note that this map is very general; it is meant as a way to visualize and conceptualize the degree to which a utility company has control over providing power to some homes and businesses and not others. The key takeaway is that customers who are not at risk of a fire could still be affected by a PSPS event due to the connections and complexities of the electric power grid.

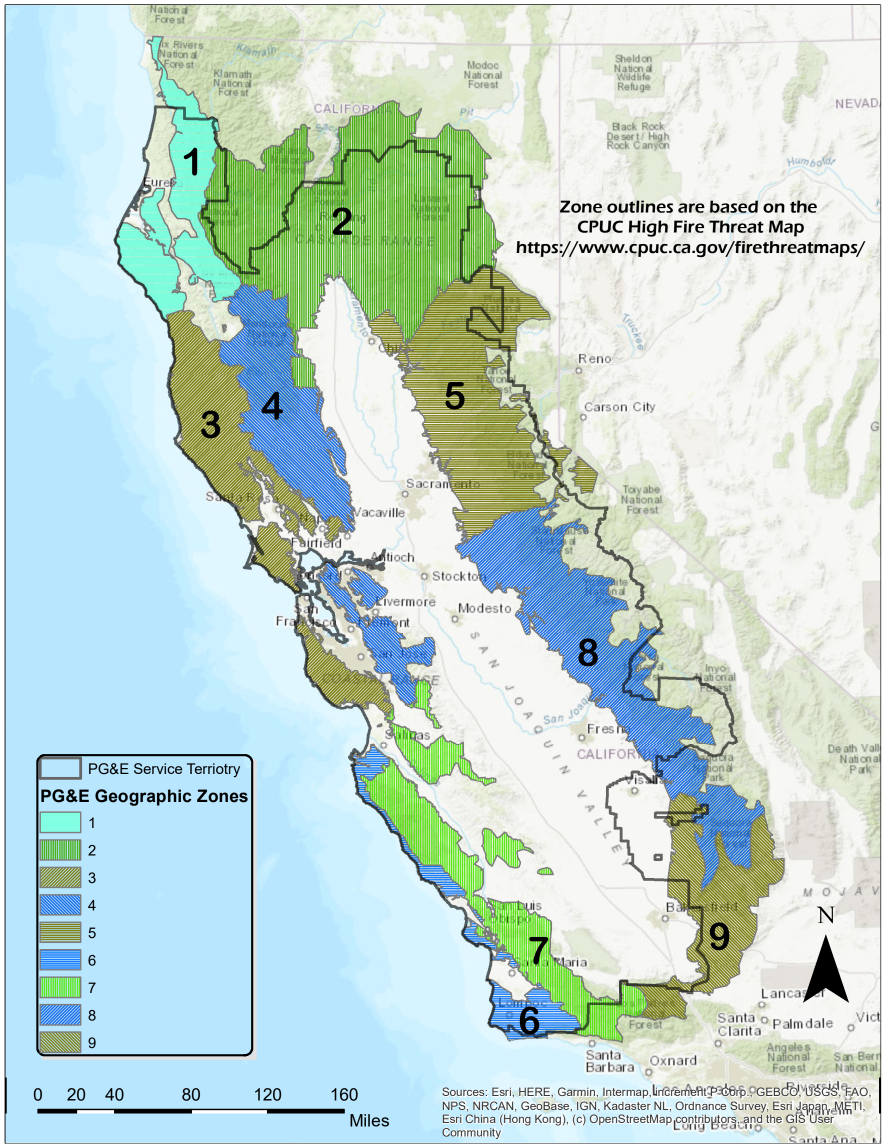

Figure 2.5. PG&E Geographic Zones. Source: Pacific Gas & Electric Company (2020c).

The CPUC Fire Threat map (Figure 2.6) defines three types of regions— Zone 1 (high hazard), Tier 2 (elevated risk), and Tier 3 (extreme risk)—which are collectively known as the High Fire Threat District (HFTD).

- *Zone 1* areas occur where there are both high tree mortality rates and critical infrastructure such as roads, utilities, and public buildings (Pacific Gas & Electric Company 2019b). Dead and decaying trees pose a direct threat to infrastructure and their removal is necessary to reduce the risk of wildfires.

- *Tier 2* areas have an elevated risk for "utility-associated" wildfires (Pacific Gas & Electric Company 2019b). These regions have a greater likelihood of fire ignition and spread compared to Zone 1 regions. Tier 2 areas would benefit from increased utility regulations, which may reduce the risk of fire (Pacific Gas & Electric Company 2019b).
- *Tier 3* areas are at extreme risk of "utility-associated" fires. These regions have the greatest likelihood of a utility-ignited fire that would impact people and property. These areas require strict utility regulation to reduce the risk of fire (Pacific Gas & Electric Company 2019b).

Similar to the previous map, the Fire Potential Index (FPI) map (Figure 2.7), shows fire risk but at a more granular scale and in a quantifiable way. The borders on this map represent Fire Index Areas (FIAs), which are sub-regions in PG&E's service territory. The FPI is an indicator of live vegetation flammability based on moisture content, and is scaled from R1 to R5, with five levels of increasing flammability and therefore, increasing fire risk (Pacific Gas & Electric Company 2019b). FPI measures are calculated daily for each FIA; days when conditions are at R4 or R5 are considered high-risk for wildfires (Pacific Gas & Electric Company 2019b). On these days, restrictions on utility operations go into effect to mitigate the potential for ignition. The shading in Figure 2.7 shows the total number of these high-risk days that occurred in a particular FIA in a year. Areas with darker shades of red are more prone to conditions that are likely to ignite a wildfire, especially through utility operations.

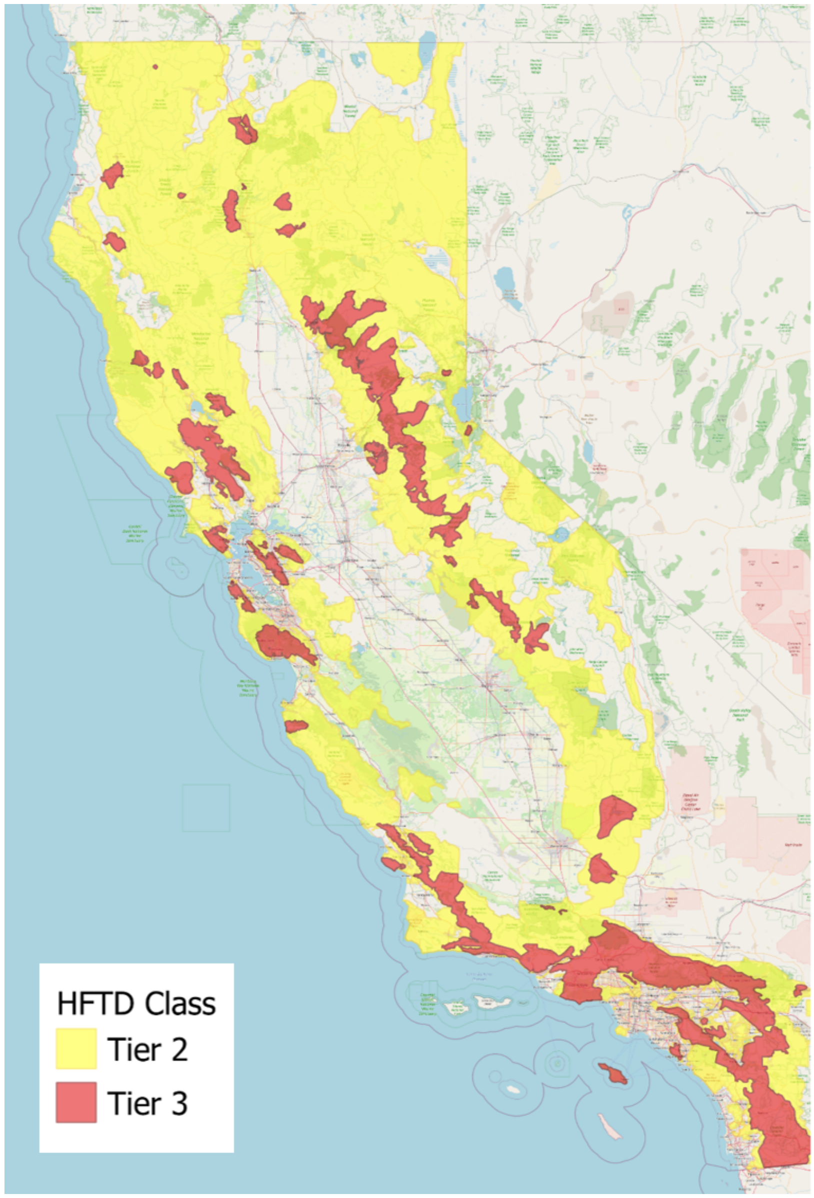

Figure 2.6. CPUC Fire Threat Map. Adapted from California Public Utilities Commission (2020).

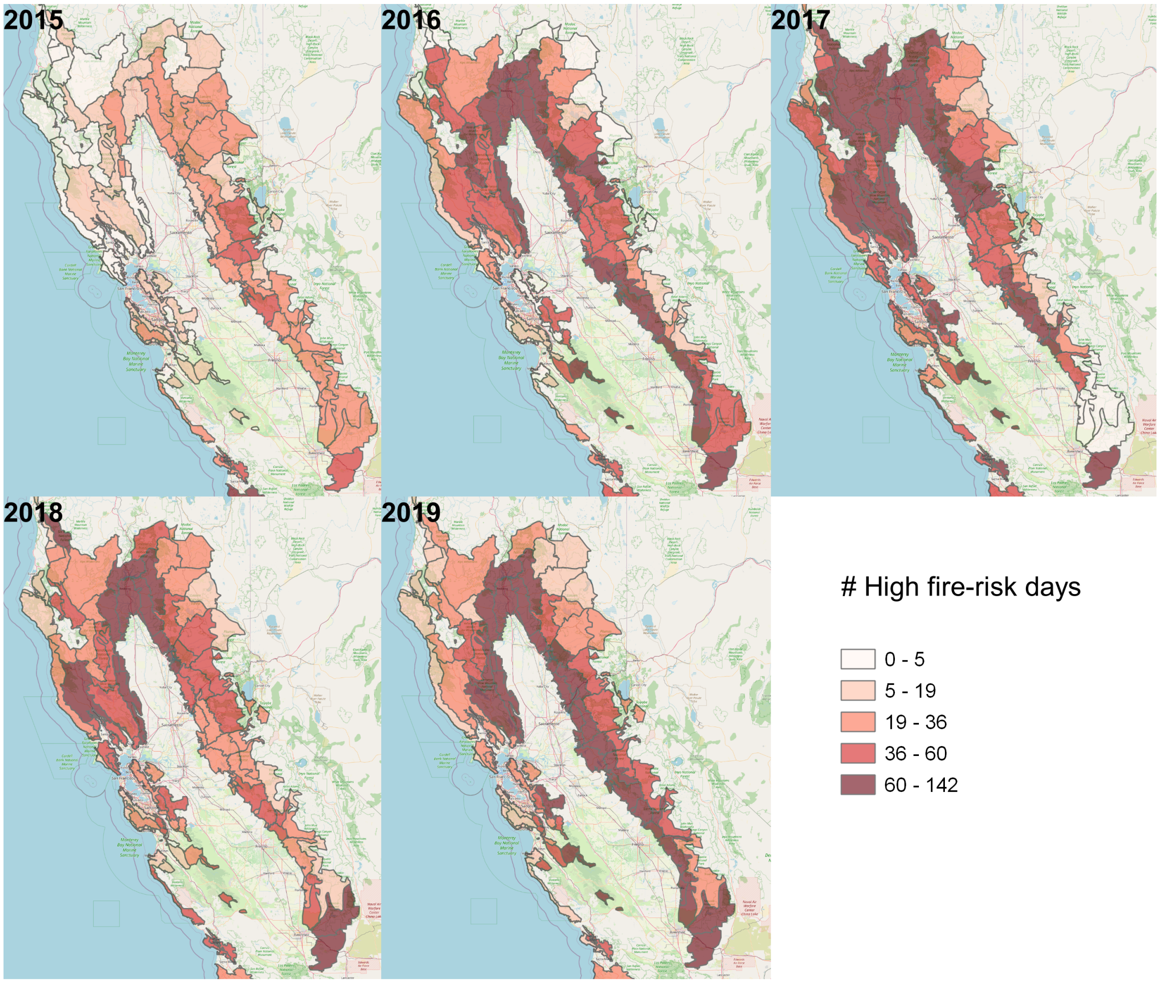

Figure 2.7. Fire Potential Index by Year. PG&E measures the Fire Potential Index (FPI) on a daily basis as a measure for fire risk. This metric is scaled from R1 to R5. At R4 and R5 conditions, restrictions on utility operations go into effect to mitigate the potential for ignition. The figure shows the number of high-risk (R4 and R5) days in the delimited Fire Index Areas (FIA). There are two patterns present across the years. The first is that there are FIAs that consistently experience more high risk days. The second is that from 2015 to 2019 there is an overall increase in the number of high risk days across all FIAs. Adapted from Pacific Gas & Electric Company (2020a).

2.3 Previous Research on PSPS-Related Topics

This section reviews selected works pertinent to the question of study. It covers fire propagation models, electric power operation, and risk mitigation that fall along a spectrum from high fidelity (high complexity) to low fidelity (low complexity).

2.3.1 Wildfire Modeling

Where a forest fire starts and how it spreads are longstanding questions that have been studied by researchers and utility companies alike. Graham et al. (2004) review the vast literature related to the topic of wildfires. Wildfire ignition and dynamics are primarily governed by three factors: (1) weather, (2) flammable fuels, and (3) the physical setting (Graham et al. 2004). Important weather characteristics are wind, temperature, precipitation, and humidity (Graham et al. 2004). Flammable fuels, which consist of live and dead vegetation and debris can vary in composition, amount, distribution, and moisture content which all influence wildfires (Graham et al. 2004). The physical setting has multiple components which should also be considered in wildfire dynamics — slope, elevation, relief, and soil (Graham et al. 2004). These factors influence wildfires over both short- and long-term timescales, and they can interact with each other in complex ways (Graham et al. 2004). All of these factors and their interactions must be considered in wildfire modeling.

Although no model or simulation can capture all of the variability and randomness of a true fire, some capture particular details better than others. With all fire spread models, there is a tradeoff between complexity of inputs and calculations versus computational effort. Wildfire studies and modeling can be split into two broad categories— (1) ignitions and (2) fire spread/dynamics. We will highlight a few references, among the vast literature on the topics, that are relevant to this thesis.

Modeling Ignitions

Xu et al. (2016) present a risk assessment of ignition occurrence near high-voltage power lines in Hubei Province, China. The authors utilize remote sensing and Geographic Information System (GIS) data from past ignition events on weather, vegetation cover, and terrain to build a logistic regression model. This model was used to create ignition probability maps along power lines, which was validated against a test set of ignition data (Xu et al. 2016).

Although the results of this case study are applied to the specific region and utilities, similar methods can be used to study ignitions elsewhere.

Massada et al. (2013) compare the performance of three ignition-distribution models with respect to prediction accuracy, variable importance, and spatial patterns. The first is a Generalized Linear Model (GLM) with a binomial response (logit link function) and variable selection based on Akaike Information Criterion (Massada et al. 2013). The remaining two models are a Random Forest (RF) and Maximum Entropy model (Massada et al. 2013). The analysis found similar model fit and variable importance across the three methods. The RF and Maximum Entropy had slightly better prediction accuracy compared to the GLM (Massada et al. 2013). Massada et al. (2013) observed the greatest difference in spatial patterns, where the Maximum Entropy model produced very different results than the other models. The authors recommend that ignition-probability analysis be conducted by either comparing results from multiple models or combining models to create an ensemble.

Modeling Fire Spread

Cortez and Morais (2007) present a data mining approach to predict the final size (burned area) of forest fires, using data collected from fires in the north-east of Portugal. Cortez and Morais (2007) build several regression models using five techniques—(1) multiple regression, (2) decision tree, (3) RF, (4) neural net, and (5) support vector machines—applied to spatial, temporal, meteorological, and fire weather index variables. The most accurate model is a Support Vector Machine with a subset of meteorological variables relating to temperature, relative humidity, wind, and rain (Cortez and Morais 2007).

Peterson et al. (2009) develops a raster fire spread model, called HFire, capable of simulating single-fire events or long-term fire systems. It is a spatial spread model that is appropriate for use on grass or shrubland terrain. The model is based on the Rothermal rate-of-spread equation, which resembles heat transfer with analogous empirically derived terms for wildfires. This equation calculates the "steady-state rate of fire spread in the direction of maximum fire spread" (Peterson et al. 2009). Complexity is added with a raster approach, which allows fire to spread between neighboring cells over multiple time steps. The simulation, with source code written in the C Programming Language, is efficient and can be used to understand the dynamics of a progressing wildfire events (Peterson et al. 2009).

Petrovic et al. (2012) implements a basic model to represent fire spread which uses queuing theory and stochastic processes. This fire spread model is used to analyze tradeoffs in fire suppression relating to timing and strength of suppression efforts. It differs from HFire primarily in its spatial modeling. The flammable terrain is broken up into discrete parcels which become part of a queueing system when they ignite. The size of the fire and rate of spread scale with the size of the queue. Although it is not a highly detailed model, it can be "used to examine basic relationships" between inputs and simulation results (Petrovic et al. 2012).

Cruz and Alexander (2019) present a "rule of thumb" for the forward rate of fire spread based solely on wind characteristics — the rate of spread of a fire can be approximated as 10% of the average wind speed present (in the same unit of measurement). Cruz and Alexander (2019) develop this simple rule by using an ordinary least squares linear regression on data published in wildfire case studies. The datasets cover fires in conifer and dry eucalyptus forests and temperate shrublands, and data on wind speed measured in the open averaged over a 10-minute time interval. The rule of thumb works best when applied to dry fuel and high wind conditions. It can be adjusted to accurately predict fire spread using other kinds of wind measurements (Cruz and Alexander 2019). It should not be used for grassland environments (Cruz and Alexander 2019).

2.3.2 Electric Power Operation

There exists a vast literature on electric power operation. For a general introduction to electric grid operation, see Wood and Wollenberg (1996). To understand the evolution of electric power operation, see O'Neill et al. (2006). This section highlights a select few references that relate to this thesis.

Salmerón et al. (2004) present a prescriptive optimization model representing the linearized operation of an electric transmission system, and use a bi-level "attacker-defender" formulation to identify worst-case disruptions to system components that result in the largest load shed (power outage) even after the operator re-balances system resources. Salmerón et al. (2009) expand this work with an efficient decomposition technique for solving this type network interdiction problem.

Nagarajan et al. (2016) present a prescriptive model for the operation of a three-phase electric distribution system and consider design options for making the system resilient to failure. Petri (2017) builds on this work to investigate the operational resilience of the electric distribution system. The model borrows from attacker-defender paradigms to minimize the amount of load not met, in an attempt to guarantee that all electricity demand is met for a distribution system. Switches in the “open” and “closed” states act as decision variables in the network model, subject to various physical constraints.

Mohagheghi and Rebennack (2015) solve a two-stage stochastic nonlinear optimization problem for operating a transmission power grid during an advancing wildfire. Specifically, they model the wildfire only as related to its effects on the transmission lines. Rather than model the fine detail of fire spread and the electric power gird separately, the authors create a coupled system with parts relevant to the question study. The model is heavily parameterized with inputs for conductor specifications, fire spread rates, atmospheric conditions, and heat transfer. Mohagheghi and Rebennack (2015) highlight the tradeoffs between making informed decisions and timely decisions in the context of effective fire mitigation.

Trakas and Hatziargyriou (2017) studies a similar question to Mohagheghi and Rebennack (2015) on an electrical distribution system (rather than transmission). They use a nonlinear approach with mixed integer linear programming and quadratic constraints to provide a solution to the operation of a distribution system against a spreading wildfire. They aim to minimize the expected social cost (in terms of load shed) in both scenarios where a fire is and is not present to point out the differences in optimal utility operations.

2.3.3 Risk Mitigation

A variety of risk frameworks and mitigation strategies are present in the literature. Here we highlight two in particular: the first in the context of wildfires affecting the wildland-urban interface; the second in the context of large-scale electricity outages.

Calkin et al. (2014) outline the principles of risk management and highlights the ability of a strong risk framework to decrease the potential for losses. The paper discusses how the effectiveness of a wildfire mitigation plan (and any plan for that matter) is mainly based on “how the problem is perceived and how the objectives are defined” (Calkin et al. 2014). The main objective, which is to mitigate risk, can be broken down into more specific ideas.

Each of these ideas can then be linked to a specific action, with a responsible agent (as an example, this could be any of the stakeholders in section 2.1.3). This kind of risk framework can be used to identify strategies of varying degrees that produce the targeted decrease in risk.

Eyer and Rose (2019) present a broader approach to risk reduction that looks at the trade-offs between mitigation and resilience. They apply this methodology to large-scale power outages. More specifically, they categorize mitigation strategies as those that preemptively reduce the possibility of power outages. They also define three stages of resilience investments which (1) reduce the dependency for electricity before the outage occurs, (2) decrease the losses during an outage, (3) decrease the recovery time after an outage occurs. Overall, they find that resilience, rather than mitigation strategies, for large-scale power outages may be better able to reduce total cost and impact on a community.

2.4 Modeling PSPS Elements

Modeling the dynamics of PSPS events requires (at least) three tasks: modeling fire spread, modeling electric power operation, and modeling the interaction between the two systems.

To date, there has been very little in modeling and analysis of PSPS events. Rhodes et al. (2020) (preprint) is the first to present the "optimized power shut-off problem" that considers the tradeoffs between preventative wildfire risk management by utility companies and the disruption to utility customers.

The first step they take is to assess wildfire risk associated with the electric power grid. Rhodes et al. (2020) assign risk values to individual components based on (1) predetermined geographic wildfire risk and (2) component characteristics (such as voltage and maintenance). Rhodes et al. (2020) assume that this risk manifests itself as an ignition probability in the direct vicinity of the component. For the purposes of this study, Rhodes et al. (2020) assume that all generators and buses have the same probability of ignition, and therefore, the wildfire risk depends only on geographic location. The ignition probability of transmission lines is a function of voltage and line length (Rhodes et al. 2020).

Each component can either be energized or de-energized. A de-energized component has zero wildfire risk. The system of components is subject to physical constraints present in an operational power grid (Rhodes et al. 2020). Rhodes et al. (2020) develop a family of constraints each for dependencies between components, generator limits, and power flow. This study focuses on direct current (DC) power flow. The overall risk of a section of the power grid is the sum of the risk values of all energized transmission lines, generators, buses, and loads (Rhodes et al. 2020).

Next, Rhodes et al. (2020) represent the impact of power-outages on customers. They measure this as the fraction of load demand delivered during the PSPS event compared to normal operations (when all lines are energized). The total load delivered is the sum of the loads carried across all components. This study also discusses an extension of this formulation where individual component loads can be weighted differently based on operational priorities (Rhodes et al. 2020). Rhodes et al. (2020) provides "hospitals or other essential services" as an example. However, for the purposes of this study, all weights are set to one (Rhodes et al. 2020).

The objective function for the optimization problem is to maximize the load delivered, while minimizing the wildfire risk as expressed by Rhodes et al. (2020) in Equation 2.1:

$$\max \ (1-\alpha)D_{total} - \alpha R_{fire} \tag{2.1}$$

where D_{total} is the total load delivered and R_{fire} is the overall wildfire risk of utility equipment. The $\alpha \in [0, 1]$ parameter captures the tradeoffs inherent to PSPS events — a small α prioritizes the load objective, while a large α prioritizes the wildfire risk objective (Rhodes et al. 2020). This summarizes what the authors called the Optimized Power Shutoff (OPS) problem, which is a mixed-integer linear program (MILP). The comprehensive model formulation can be found in Rhodes et al. (2020).

As a basis for comparison, Rhodes et al. (2020) develop two additional heuristics which model the PSPS decision-making process. Each heuristic is implemented as a two-step process. The first step determines which components will be de-energized, based only on the wildfire risk (Rhodes et al. 2020). The second step aims to maximize the total load delivered, given the subset of energized components that remain (Rhodes et al. 2020). The two heuristics apply to the first step and differ in the way in which wildfire risk is used to make decisions:

1. Area heuristic: Given that the power grid is partitioned into operational areas, the overall risk of each area is calculated. If this value is greater than a threshold risk value, then all components in the area are de-energized.
2. Transmission heuristic: If the risk value of an individual transmission line exceeds a threshold risk value, then the line is de-energized.

The second step is implemented as a maximum load delivery optimization problem with similar constraints to the OPS (Rhodes et al. 2020). It is also a MILP.

The three model formulations— OPS, area heuristic, transmission heuristic— are applied to the IEEE RTS-GMLC 96-bus test case, located in an area covering Los Angeles, Las Vegas, and the north-western edge of Arizona (Rhodes et al. 2020). The authors create a simple wildfire risk map, based on local news reports, which they overlay on the notional electric power grid. The map shows four levels of possible fire risk: low-, medium-, high-, and extreme-risk (Rhodes et al. 2020). For the OPS and transmission heuristics, rather than solve for a single optimal solution, the authors choose to solve the problem for a range of α values (for the former) and a range of risk-threshold values (for the latter) to create a Pareto frontier of solutions that shows the tradeoffs between wildfire risk and electric power disruption. For the area heuristic, a single threshold risk value was chosen to target the single extreme-risk area on the map.

The results reveal four primary insights, as discussed by Rhodes et al. (2020).

1. The three model formulations provide different levels of "targeting". The area heuristic is the least targeted method; it shuts off too great of an area which results in the greatest load shed and the smallest reduction in wildfire risk, compared to the other models. The transmission heuristic is more targeted as it considers risk for individual assets but it does not consider the consequences of shutting them off. The OPS problem is the most targeted approach as it considers both the wildfire risk and downstream effects of shutting off power to certain components.
2. The OPS problem consistently provides better solutions (less load shed and greater risk reduction), compared to the other two methods.
3. The OPS problem allows for solutions where high-risk lines remain energized, given that they carry a relatively large amount of power.
4. The electric power grid topology for the lowest risk solution has a tree-like, or radial,

structure.

This study is an important first step towards understanding the benefits and costs of power shutoffs as an avenue for wildfire risk mitigation. However, the formulated OPS problem is missing crucial details that should be supplemented in future work. Two of the most important factors in determining the probability of ignition and the potential for fire spread are the weather and fuels, both of which are not considered by Rhodes et al. (2020). In terms of measuring the impact of a PSPS event, Rhodes et al. (2020) does not consider the duration of an outage, or the number or of type of customers who lose power. Additionally, the potential for electric faults that occur after de-energization and/or during the restoration process are not considered in the risk calculations. Incorporating these details requires a vast amount of knowledge and data on the particular power grid and landscape being studied.

The approach of Rhodes et al. (2020) considers different levels of fidelity for different part of the problem. There is a spectrum of fidelity that should be considered when modeling; the spectrum can be broken into three broad categories (Figure 2.8). High-fidelity models most closely resemble reality; they require large amounts of input data and complex computations to capture the details of complicated behavior. Low-fidelity models require less input data; they simplify complicated behaviors, but still allow for Monte Carlo-type analyses to gain insight on real-world processes. High-fidelity models for all three tasks are the ultimate goal for PSPS stakeholders and should be used as decision-making tools in the future. However, these computationally-intensive methods are beyond the scope of the efforts of this thesis. Low-fidelity models were considered for this thesis, but gaps were found in the required input knowledge and data. Rather than focus on high- or low-fidelity models, this thesis seeks to close that gap and examine the data necessary for more complicated modeling.

(wildfire) (electric power)

increasing complexity

	Research Question:	What burns?	What goes without power?
Type of Analysis	High-Fidelity Model	Large amounts of input data; complicated mathematics; detailed simulation	
		Fire spread models that incorporate wind, fuel levels and moisture, humidity, terrain, etc. (e.g. Hfire)	DC-OPF linearized model at the tranmission level and 3-phase AC model at the distribution level; details on PG&E power grid control structure
	Low-Fidelity Model	Less input data; approximated mathematics; Monte Carlo type simulation	
		Approximation of wildfire dynamics using wind-speed rules, raster-based models, etc.	Electricty flow approximated as "upstream" and "downstream" of control points; grid structure simplifed into network of adjacent/connected lines
	Pre-Model	Analysis of limited data; regreession-type analysis; simple sampling of data	
		Analysis of historic weather data and weather-related criteria used in decision-making	Analysis of historic PSPS data on de-energization, power restoration, and consequences

Figure 2.8. Hierarchy of PSPS Model Fidelity. Wildfire and electric power grid models can vary in fidelity based on the amount of input data and complexity of simulation.

CHAPTER 3:
Exploratory Data Analysis

Since 2015, PG&E's electrical equipment has sparked over 2,000 ignitions (Pacific Gas & Electric Company 2019g). Many of these ignitions grew into wildfires, 30 of which burned over 100 acres each (Pacific Gas & Electric Company 2019g). Some of these fires, shown in Table 3.1, are among the largest and deadliest in California's history. As a result of these catastrophic wildfires, PG&E faced lawsuits, filed for bankruptcy in 2019, and came under increased scrutiny from regulatory agencies and California residents (Pacific Gas & Electric Company 2020b). PG&E's publicly available reports and data were closely examined and hundreds of additional data request were made by various agencies. Altogether, this array of data provides a broad and detailed view of the utility company's electric power infrastructure, operations, and decision-making process.

Table 3.1. PG&E-Ignited Fires from 2015 to 2019. Some of these are among the largest and/or deadliest in the history of California.

Fire Name	Date	County	Acres	Structures Lost/Damaged	Deaths
Butte Fire	Sept. 2015	Butte	70,868	921	2
Tubbs Fire	Oct. 2017	Napa, Sonoma	36,807	5,643	22
Atlas Fire	Oct. 2017	Napa, Solano	51,624	781	6
Redwood Valley Fire	Oct. 2018	Mendocino	36,523	590	9
County Fire	June 2018	Napa, Yolo	90,288	29	1
Camp Fire	Nov. 2019	Butte	153,336	18,804	85
Kincade Fire	Oct. 2019	Sonoma	77,758	434	0

3.1 Data Collection

As a starting point, we gather data from PG&E and other publicly available sources on wildfire weather, the electric power grid, and the impact of PSPS events. We use this data to construct multiple datasets to support this study. The data collected is in three forms—GIS files (e.g., .gdb, .dbf, .shp), comma-separated value data files (i.e., .csv), and written reports.

This data comes from four different sources: (1) PG&E's PSPS reports to the CPUC, (2) PG&E's 2020 Wildfire Mitigation Plan (WMP), (3) additional data requests that resulted from the WMP, and (4) the other sources.

PSPS Reports to the CPUC

Following every PSPS event, PG&E is required to make a report to the CPUC describing "key information including the rationale, sequence of events, and activities for [the] PSPS event" (Pacific Gas & Electric Company 2019d). These reports include information on the power-restoration process.

2020 Wildfire Mitigation Plan (WMP)

The WMP is a report authored by PG&E that provides details and lessons learned from the 2019 wildfire season, along with plans for future programs and safety measures (Pacific Gas & Electric Company 2020a). It includes supplemental data files which are referenced in the written report, including geospatial files for all PSPS events that occurred in 2019. These files provide the circuits that were planned for de-energization for each PSPS event, as well as the following metrics: HFTD-class of the affected circuit, start date and time of the outage, duration of outage, total number of customers affected by the outage, and the number of each type of customer (i.e., residential, commercial, medical baseline) serviced on each circuit. The WMP also provides a geospatial data on fire ignitions created by PG&E's electrical equipment from 2015-2019. This data includes site of ignition, final fire size, and the suspected cause.

Data Requests

In response to the WMP, several agencies requested additional data, which PG&E also made publicly available. A wide range of inquiries were made, making this data source a valuable resource. We acquired geospatial data on PG&E's electric power grid (locations of both transmission and distribution assets), which included metadata such as ignition and failure probabilities, line-miles in each HFTD-class, and scores and ranks related to wildfire risk. Also included is geospatial data for:

- PG&E's administrative boundaries — this is a hierarchical structure that starts at the entire service territory, splits into regions, divisions, and finally districts;

- Customer location — this is a one-mile squared resolution grid with counts of customers within each square; and
- Wildfire-related weather — this includes information on RFW days and weather stations with wind measurements.

Other Sources

We use GIS files from the CPUC that define the HFTD (discussed in Section 2.2). We also use historic electricity usage data from the California Independent System Operator (CAISO).

3.2 Datasets

In this section, we take a closer look at data on the following topics: (1) the electric power grid, (2) utility-caused ignitions, (3) wildfire weather, and (4) past PSPS events.

3.2.1 Electric Power Grid

PG&E's electric power grid services customers across north, central, and southern California. The service territory is divided hierarchically into regions (largest areas), divisions, and districts (smallest areas), shown in Figure 3.1 (Pacific Gas & Electric Company 2019h). These areas are often referenced in PSPS reports as decision-making hubs for both PG&E and local authorities.

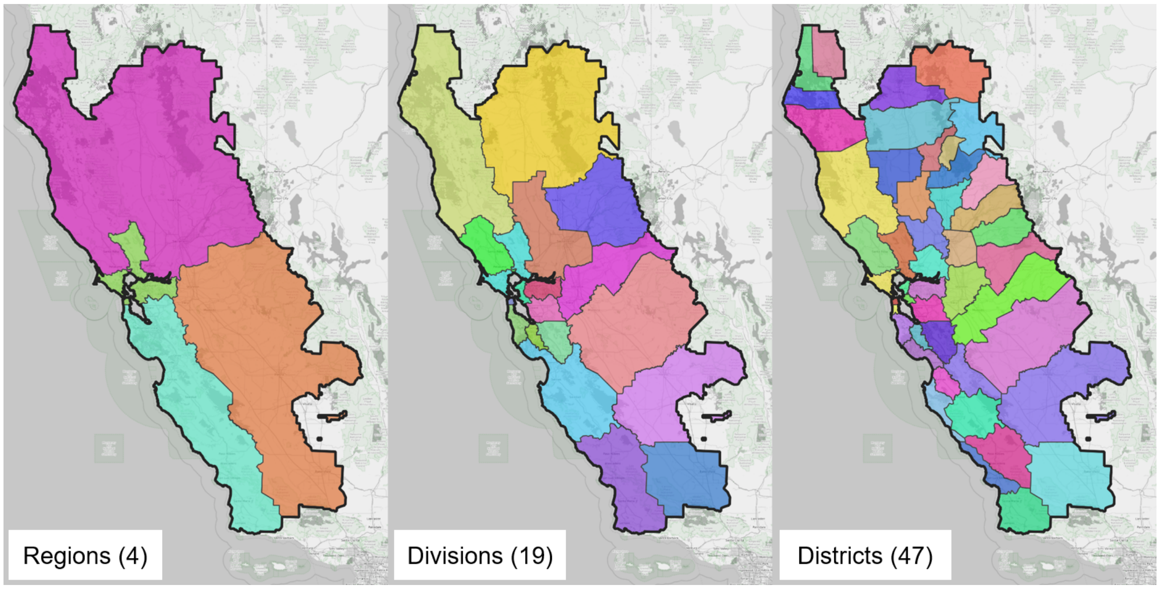

Figure 3.1. PG&E Geographic Boundaries. PG&E divides their service territory (black outline) into operating areas based on a hierarchical structures. Regions (left), the largest areas, are split into divisions (middle). Divisions are further split into districts (right), the smallest areas. The numbers in parentheses are the total number of each kind of area. Adapted from Pacific Gas & Electric Company (2019h).

PG&E provides power to over four million service points in California (Pacific Gas & Electric Company 2019j). The location of these is shown in Figure 3.2 at the square-mile resolution. Knowing the location of customers is necessary for utility companies to identify the demands and risks present in a region. The distribution of customers across the service territory is not uniform. There are both sparsely and densely populated areas which have different energy demands. The terrain and vegetation around customers also differs. Customers may be in very urban areas with little vegetation, or they may be in areas interspersed or adjacent to heavily vegetated areas. The latter of these is the WUI, defined by the Forest Service as "any area where humans and their development meet or intermix with wildland fuel" (Stein et al. 2013). One example of this is the North Bay region surrounding Napa (Figure 3.3). This area consists of pockets of densely populated areas overlapping with or directly adjacent to HFTD Tier 2 and Tier 3 zones. Customers in these areas are not only at risk of naturally-ignited wildfires, but are also especially prone to utility-ignited fires.

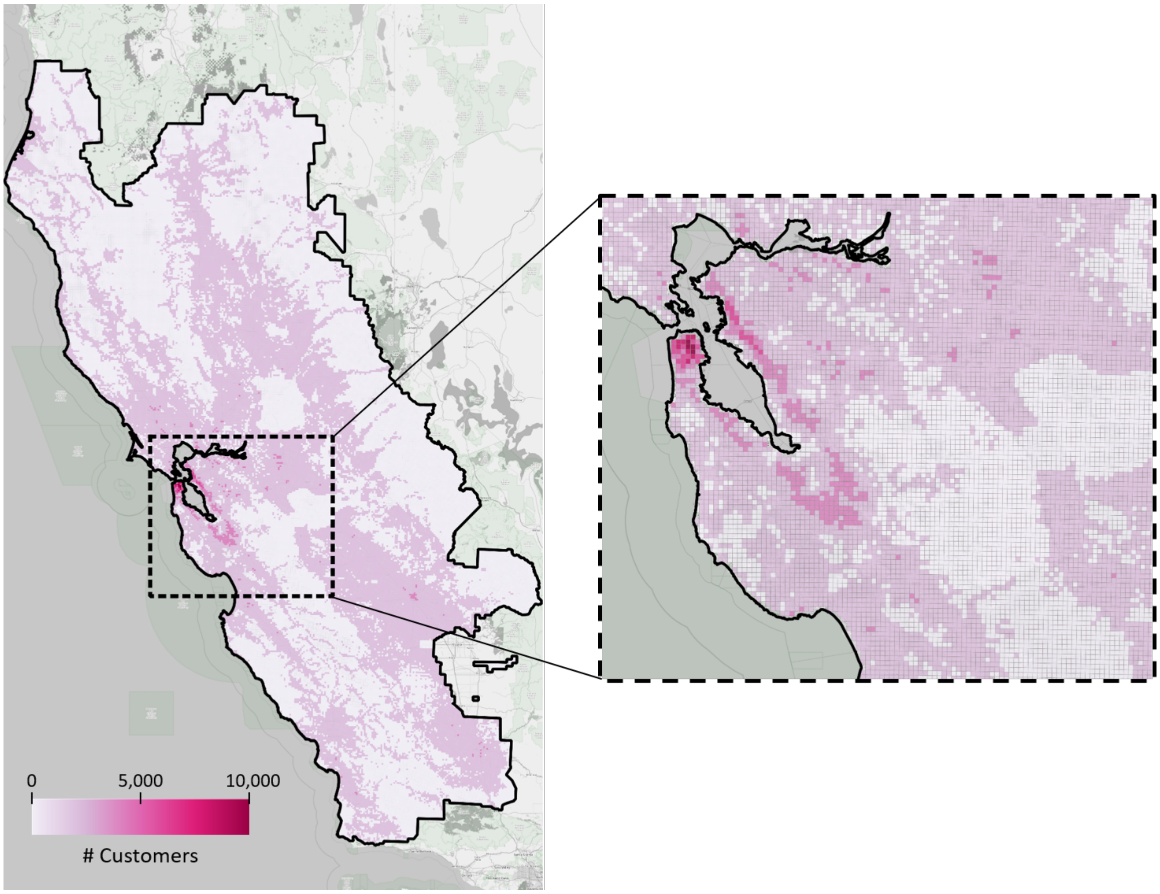

Figure 3.2. PG&E Customers Across Service Territory. Customer data is available at the square mile resolution. A close up of the Bay Area and Santa Cruz Mountains is shown to illustrate the range in customer density. Adapted from Pacific Gas & Electric Company (2019j).

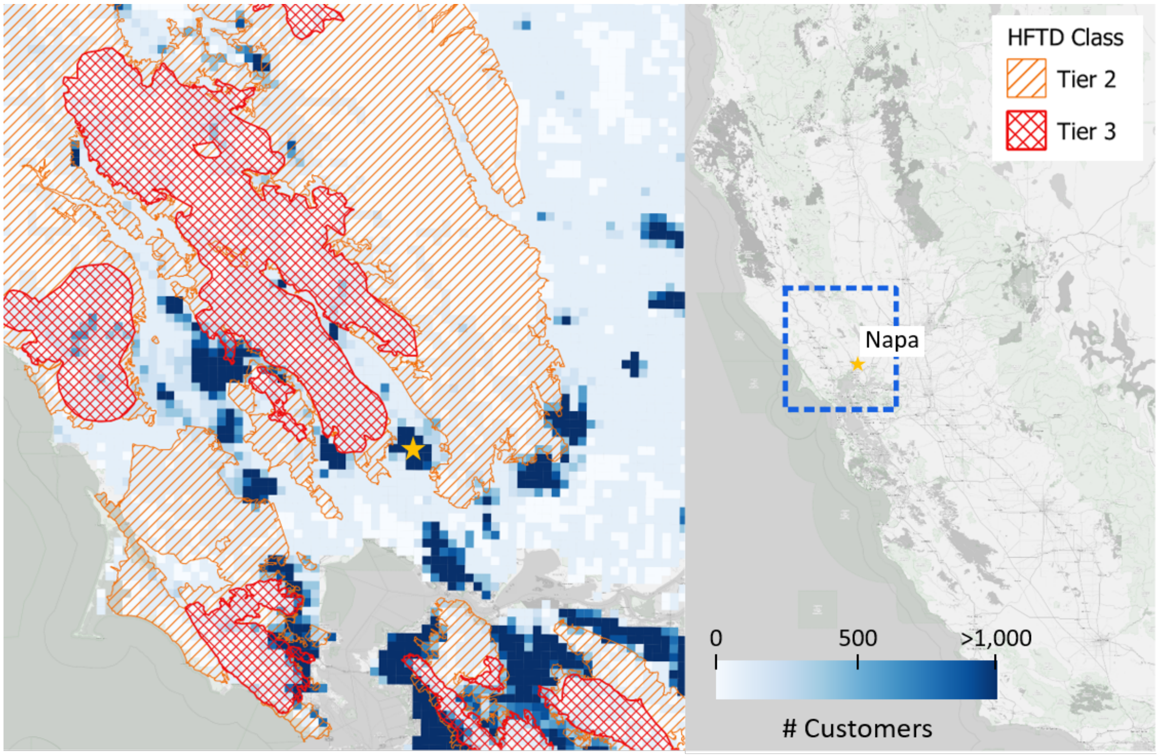

Figure 3.3. Wildland Urban Interface. The WUI is an area where human development is adjacent to or coincides with wildfire-prone areas. The map shows part of the North Bay area around Napa. PG&E services densely populated areas (shown in dark blue) in areas that overlap with Tier 2 and Tier 3 HFTD areas. Not only does this mean electric lines must traverse wildfire-prone areas, but it also means that large groups of people are in danger of potential wildfires. Adapted from Pacific Gas & Electric Company (2019j) and California Public Utilities Commission (2020).

The electric power grid operates on three levels: (1) generation, (2) transmission, and (3) distribution. The network of generation plants, transmission lines, and distribution circuits must have the capacity to reach all customers in all areas. In simplest terms, the flow of electric power starts at one of the natural gas/oil, coal, nuclear, or renewable energy generation plants that PG&E wholly or partially owns (an example is shown in Figure 3.4). It is then carried across the state via transmission lines, and finally to homes and businesses on distribution circuits.

This thesis does not consider data on the generation sector, as it is not directly relevant to

PSPS events. The transmission and distribution sectors are described in greater detail in the following sections.

Figure 3.4. Moss Landing Power Plant. The natural gas powered electricity plant located in Moss Landing is an example of one of the many generation plants in the state of California utilized by PG&E. The satellite map (left) shows where the transmission lines start. Some of the areas they carry electric power to are Santa Cruz to the north and Monterey/Salinas to the south. (left) Adapted from Pacific Gas & Electric Company (2019a). (right) Source: Google Maps and Wikipedia (2020).

Transmission

PG&E operates 2,356 transmission lines across its service territory (Pacific Gas & Electric Company 2019a). These high-voltage overhead lines traverse miles of HFTD Tier 2 and Tier 3 zones. PG&E ranks individual circuits in terms of wildfire ignition risk. The utility company calculates a risk score that is composed of multiple sub-scores based on wildfire, capacity, reliability, PSPS events, and safety (Pacific Gas & Electric Company 2019a). The scores assigned to each transmission line are shown in Figure 3.5. A low numeric score for transmission lines corresponds to a low cardinal rank score—the transmission line with rank one is considered the highest wildfire risk asset by the utility company. The minimum and maximum risk scores are 81 and 1450, respectively. The number of lines classified which are considered high-risk (shown in purple in Figure 3.5) are relatively few in number, but make up a large proportion of the total transmission line-miles.

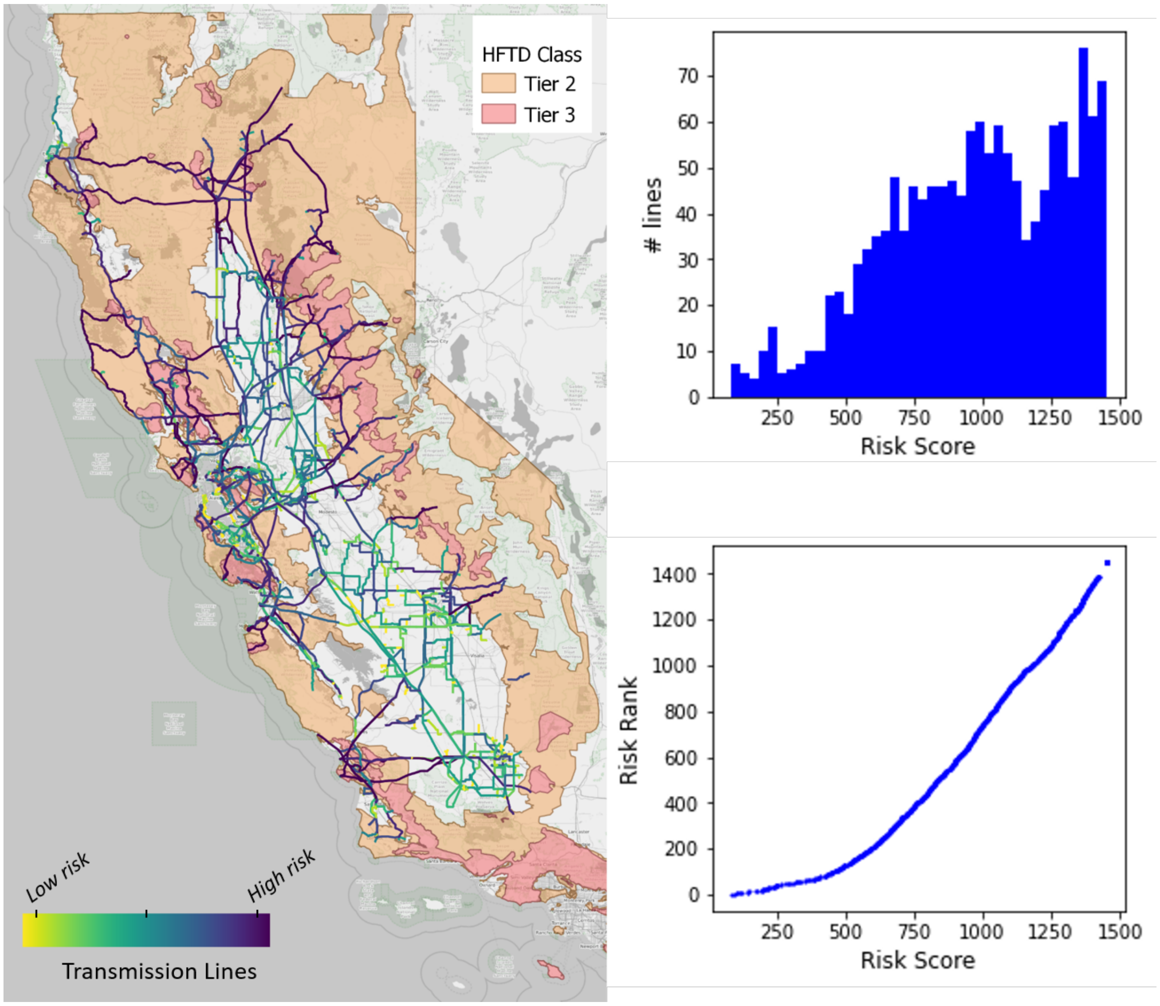

Figure 3.5. Electric Transmission. The map on the left shows all PG&E-operated transmission lines colored by risk score. The plots show the distribution of risk scores (top right) and their relationship to the rank assigned by PG&E (bottom right). The scoring scheme for transmission risk assigns lower numerical values to higher risk assets. The lowest rank (lowest score) corresponds to the highest risk asset. Adapted from Pacific Gas & Electric Company (2019a) and California Public Utilities Commission (2020).

Distribution

PG&E operates 3,390 distribution circuits across its service territory (Pacific Gas & Electric Company 2019a). Similar to the risk quantification for transmission lines, a scoring scheme is used to rank individual distribution circuits in terms of wildfire ignition risk. The scores assigned to each distribution circuit are shown in Figure 3.6. A high risk score for distribution circuits corresponds to a low cardinal rank score—the distribution circuit with rank one is considered the highest wildfire risk asset by the utility company. The minimum and maximum risk scores are 0 and 53.4, respectively.

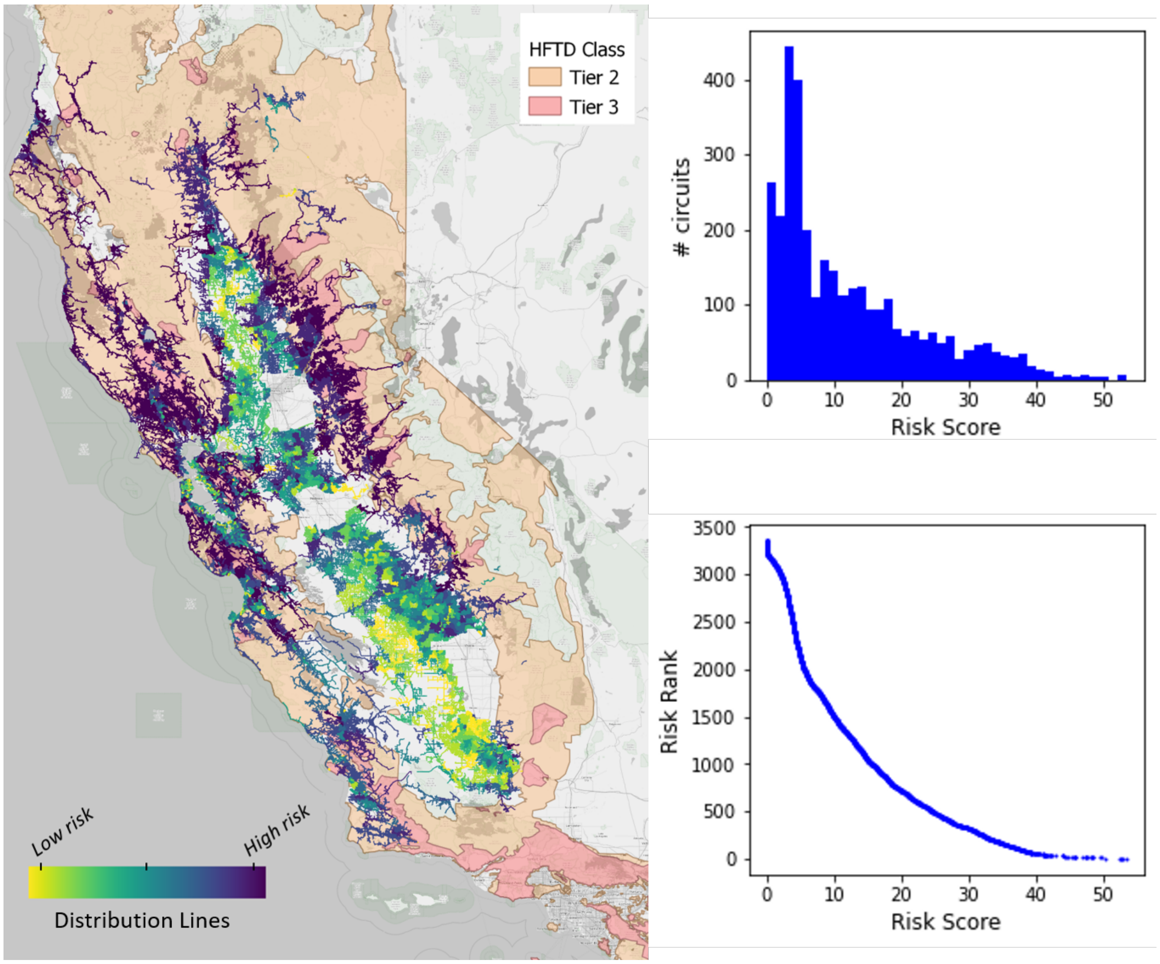

Figure 3.6. Electric Distribution. The map on the left shows all PG&E-operated distribution lines colored by risk score. The plots show the distribution of risk scores (top right) and their relationship to the rank assigned by PG&E (bottom right). The scoring scheme for distribution risk assigns higher numerical values to higher risk assets. The lowest rank (highest score) corresponds to the highest risk asset. Adapted from Pacific Gas & Electric Company (2019a) and California Public Utilities Commission (2020).

One of the factors that contributes to a high risk score is the presence of vegetation in close proximity to overhead lines. Distribution circuits crossing through HFTD zones, especially longer stretches of lines, tend to be at greater risk for this reason. Figure 3.7 shows the spread of the proportion of HFTD miles per distribution circuit (Pacific Gas & Electric Company 2019f). Although the majority of circuits are entirely outside of HFTD zones, the next single largest group of circuits is almost entirely inside of HFTD zones (a proportion of at least 0.9). Approximately 25% of all distribution circuits are partially inside Tier 2 or Tier 3 areas. Among the circuits in the HFTD, PG&E provides a separate risk score based only on vegetation. Figure 3.8 shows this score for 687 circuits in the power grid. The average score for the 392 circuits in Tier 2 regions is 0.0081. The average score for the 295 circuits in Tier 3 regions is 0.0724.

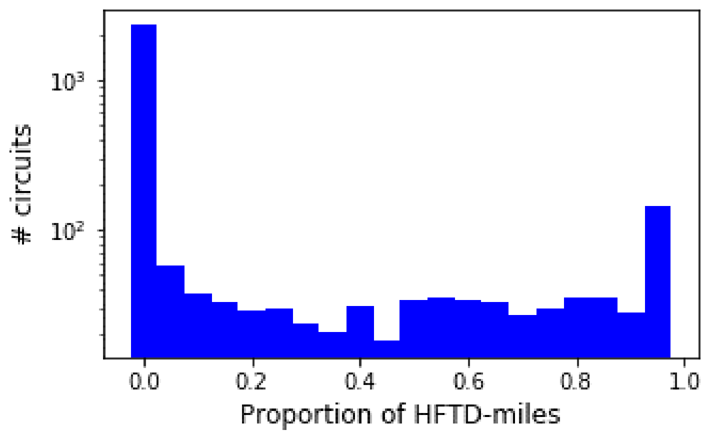

Figure 3.7. Distribution Circuit-mile Composition. Circuits with proportion 0 of HFTD-miles are entirely outside of any HFTD areas. Circuits with proportion 1 of HFTD-miles are entirely inside of any HFTD areas. Circuits with proportions between 0 and 1 have spans both inside and outside of HFTD areas. Adapted from (Pacific Gas & Electric Company 2019f).

PG&E also considers reliability in its wildfire ignition risk score. Figure 3.9 shows the distribution of failure probabilities for a subset of distribution circuits (Pacific Gas & Electric Company 2019k). The failure probabilities represent the projected likelihood of target asset failure in the next year.

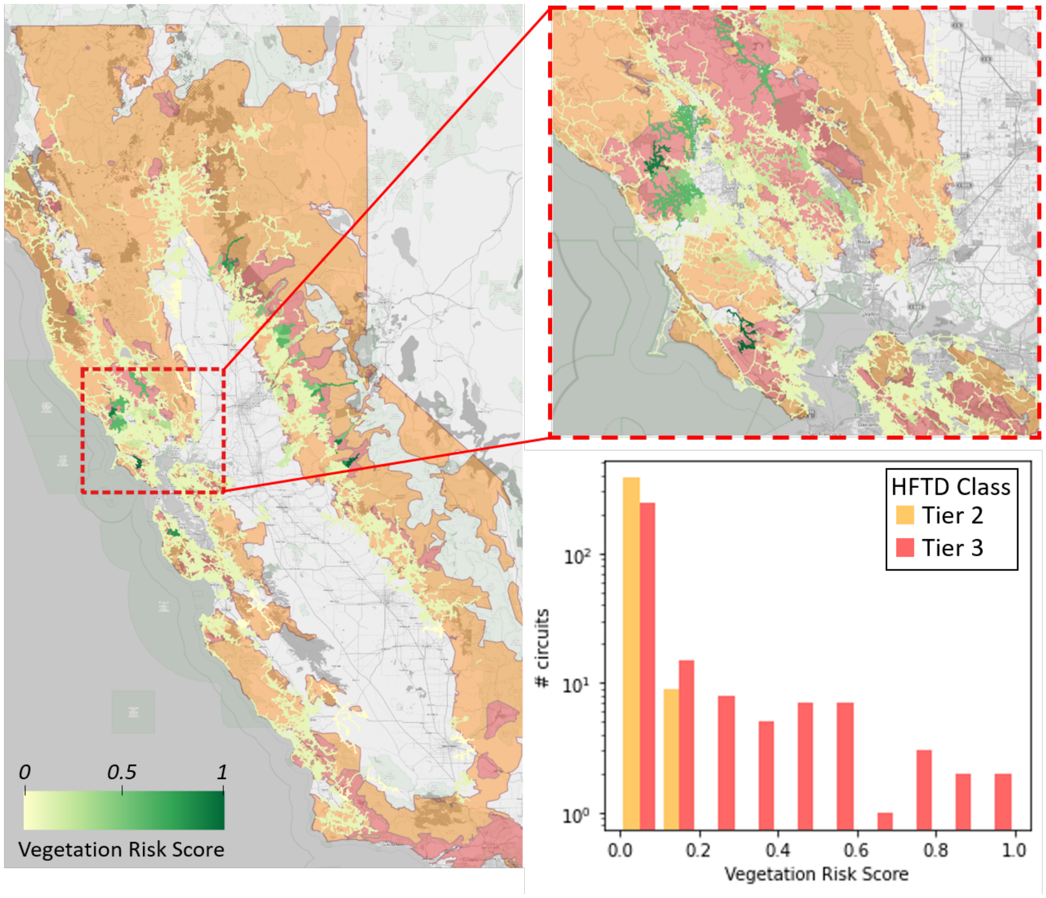

Figure 3.8. Vegetation Risk Score. The map shows the vegetation risk score for circuits in the HFTD shaded from light green (low risk) to dark green (high risk). The plot show the distribution of risk scores for Tier 2 and Tier 3 regions within the HFTD. Adapted from Pacific Gas & Electric Company (2019a) and California Public Utilities Commission (2020).

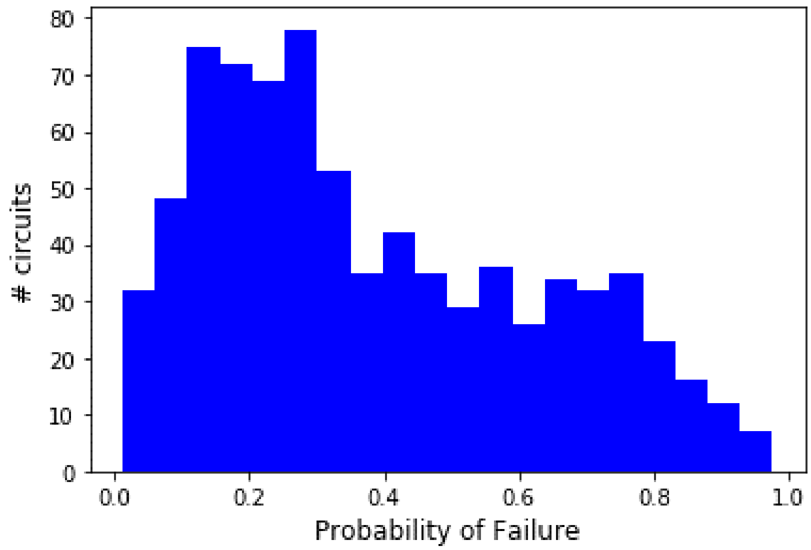

Figure 3.9. Failure Probability for Distribution Circuits. PG&E has provided failure probabilities for 789 distribution circuits. This probability represents the projected likelihood of the target asset failing in the next year. Adapted from (Pacific Gas & Electric Company 2019k).

It is useful to examine groups of distribution circuits that may be interconnected in the same region or division. Table 3.2 shows aggregate statistics for circuits at the division-level. The total mileage in HFTD zones and the average wildfire ignition risk score can indicate divisions and regions that are at a higher wildfire risk and more likely to be involved in a PSPS

Table 3.2. Summary of Distribution Characteristics. Aggregate statistics are shown by division for PG&E-operated distribution lines. A low risk score corresponds to assets which are considered less of a risk with respect to wildfires. Adapted from Pacific Gas & Electric Company (2019a) and Pacific Gas & Electric Company (2019h).

				Risk Score		
		# Circuits	Total HFTD-miles	Min.	Avg.	Max.
Region	Division					
Bay Area	Diablo	146	276.12	0	16.3	41.7
	East Bay	242	293.45	0	8.7	45.9
	North Bay	98	827.58	0	18.0	50.2
	San Francisco	277	0	0	6.5	33.5
Central Coast	Central Coast	150	1,355.01	0	12.2	38.2
	De Anza	149	607.27	0	10.6	47.5
	Los Padres	89	1,833.65	0	13.5	31.5
	Mission	152	248.64	0	14.0	48.4
	Peninsula	218	433.20	0	10.8	45.9
	San Jose	158	307.23	0	10.9	49.7
Central Valley	Fresno	338	821.43	0	7.6	33.9
	Kern	244	122.97	0	6.1	29.8
	Stockton	201	1,488.82	0	11.7	52.7
	Yosemite	181	3,148.28	0	12.2	47.3
Northern	Humboldt	104	3,156.97	0.7	27.7	44.1
	North Valley	161	3,756.25	0.2	17.8	48.1
	Sacramento	147	152.07	0	9.8	36.8
	Sierra	172	5,056.39	0.7	20.2	53.0
	Sonoma	93	1,624.07	0.0	24.1	53.4

3.2.2 Past Ignition Events

This section examines data for 2,451 ignition events from 2015-2019, as illustrated in Figure 3.10. The data covers ignition characteristics, such as location, area burned, causes, and equipment involved. Many of these characteristics contain a significant amount of missing values, which we indicate in subsequent figures and tables.

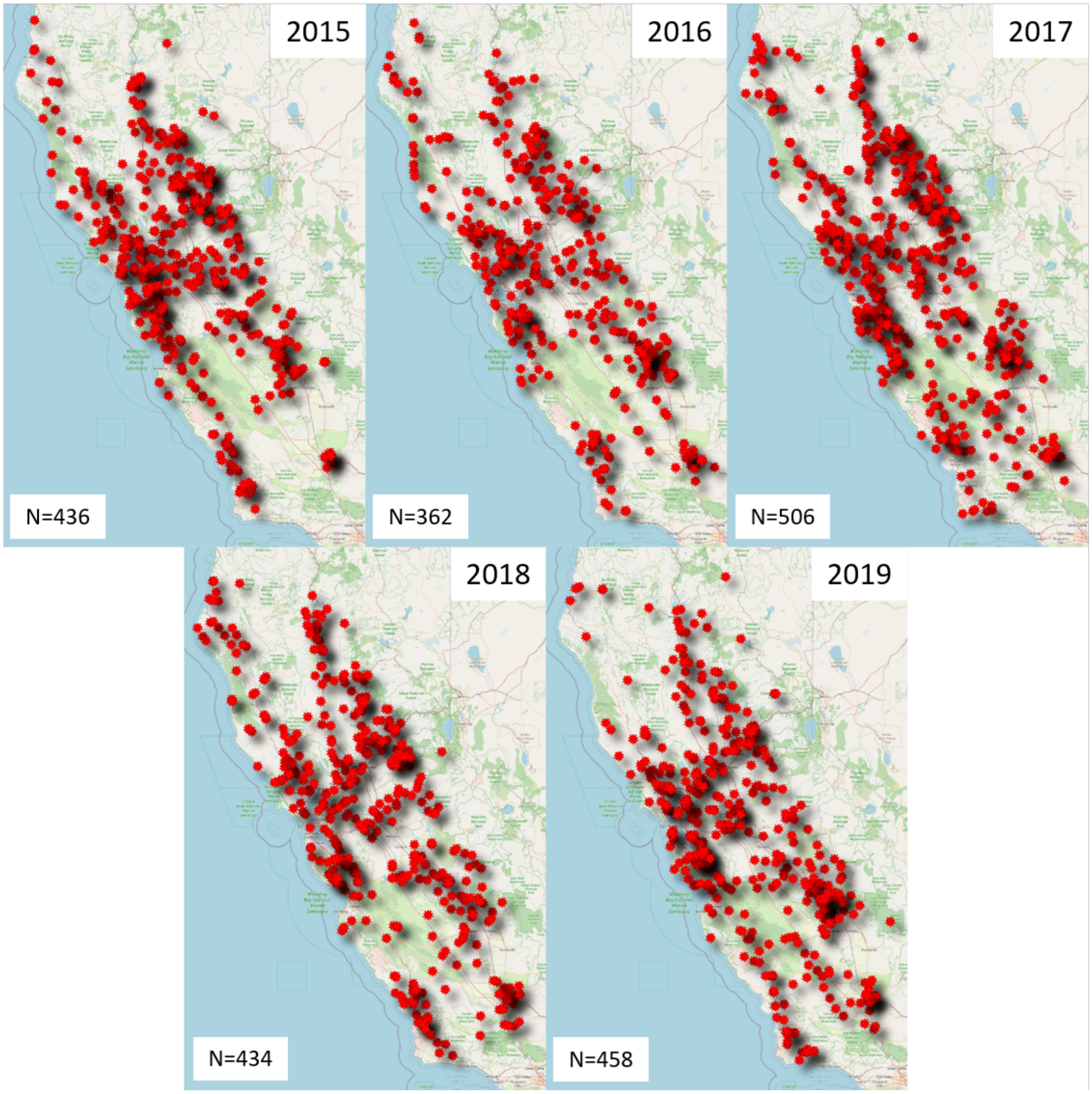

Figure 3.10. Ignition Events by Year. The number shown in the bottom left corner of each map represents the total number of ignition events in the given year. Adapted from Pacific Gas & Electric Company (2019g).

Figure 3.11 shows that utility-caused ignitions can occur in a variety of locations depending on the type of line, as well as the terrain and materials surrounding a line. Figure 3.12 shows ignitions on both transmission and distribution lines in two distinct areas of California.

By Section of Power Grid	
Distribution	0.950
Transmission	0.050
Substation	> 0.001

By Land Use	
Rural	0.636
Urban	0.174
N.A.	0.190

By HFTD class	
non-HFTD	0.682
Zone 1	0.002
Tier 2	0.221
Tier 3	0.096

By Material Type	
Vegetation	0.778
Building	0.018
Other	0.015
N.A.	0.190

Figure 3.11. Proportion of Ignition Events by Location. Adapted from Pacific Gas & Electric Company (2019g).

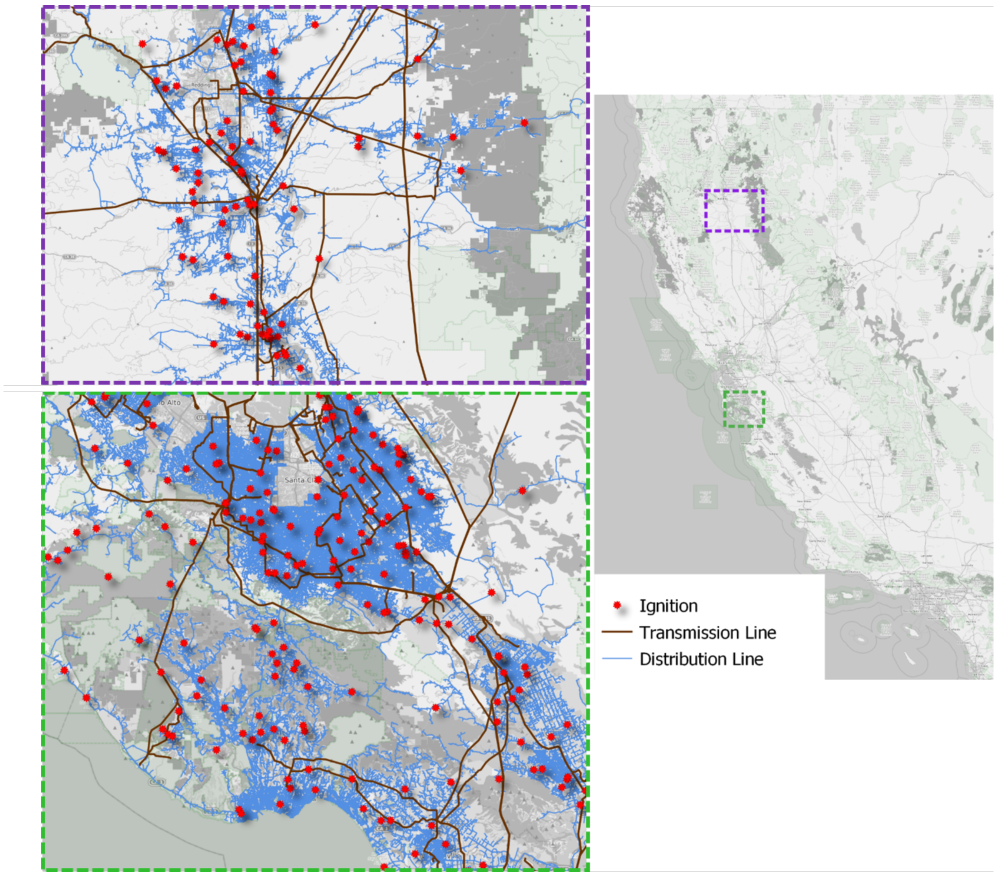

Figure 3.12. Ignition Events on Power Lines. Ignition events can occur on both transmission and distribution lines. The Sierra Foothills area (upper left) has a relatively sparse distribution network. The Santa Cruz Mountains area (bottom left) has a relatively dense distribution. In both regions, many more ignition events have occurred at the distribution level, rather than transmission. Adapted from Pacific Gas & Electric Company (2019g) and Pacific Gas & Electric Company (2019a).

Ignitions on utility equipment have the potential to start wildfires of varying sizes. Figure 3.13 shows the proportion of ignition events by the total area burned (fire size). PG&E provides fire size as a categorical (rather than numeric) variable in this data set. Several of the original categories were ambiguous and overlapping; we cleaned the data and combined categories enough so that they would be easily interpreted. Fire size is primarily given as an area (in acres). For measurements given in meters, we assume the fire was contained to the power line.

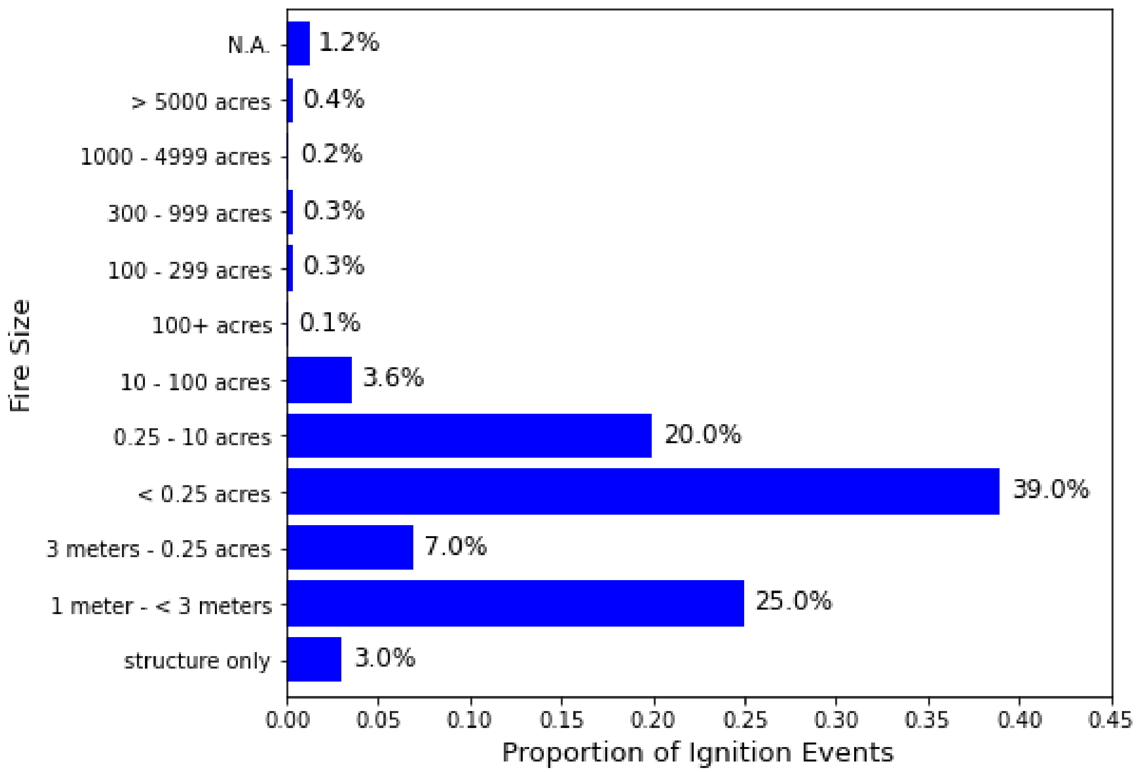

Figure 3.13. Total Burned Area. The plot shows the distribution of final burned area for utility-ignited fires from 2015 to 2019. The fire size appears in increasing order from bottom to top. Adapted from Pacific Gas & Electric Company (2019g).

Additionally, ignitions can lead to outages either due to damaged equipment or in response to a spreading fire. Of the ignitions in this data set, 88.5% resulted in some form of customer outage. Figure 3.14 shows the distribution of outage durations.

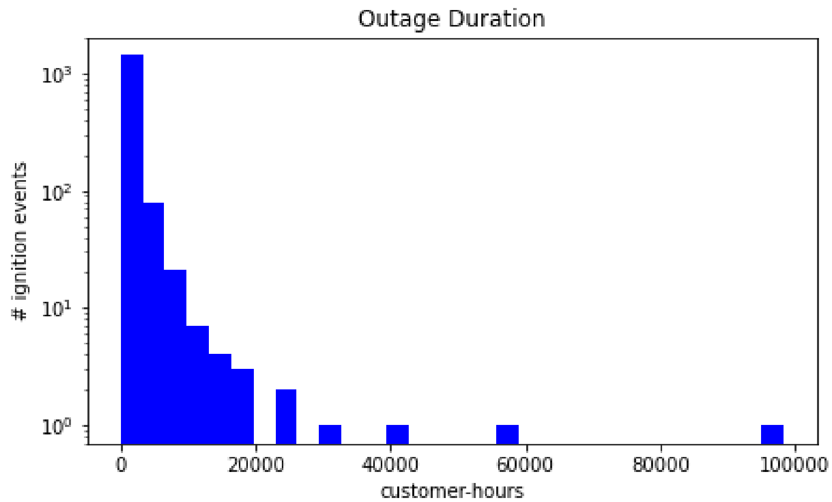

Figure 3.14. Outage Duration. The plot shows the distribution of customer-hours of a power outage that resulted from a utility-ignited fire. Adapted from Pacific Gas & Electric Company (2019g).

Many different malfunctions, failures, or unexpected events can create ignitions on electrical equipment (Table 3.3). The root cause of an ignition often depends on the type of electrical equipment (Table 3.4), associated voltage (Table 3.5), and the weather conditions. The majority of ignition events did not involve a wire-down incident (Table 3.6), although they often coincided with weather warnings (Table 3.7).

Table 3.3. Ignition Initiating Event. The table shows the proportion of total ignitions caused by various events. Adapted from Pacific Gas & Electric Company (2019g).

contact from object	0.451
equipment/ facility failure	0.299
N.A.	0.222
vandalism/theft	0.010
wire-wire contact	0.009
other	0.005
contamination	0.004
third party equipment on pole	> 0.001

Table 3.4. Type of Electrical Equipment. The table shows the counts of electrical equipment cross-tabulated by the kind of structure (overhead, padmounted, or subsurface) and the specific asset involved with ignition. Adapted from Pacific Gas & Electric Company (2019g).

	Overhead	Padmounted	Subsurface	N.A.	Totals
capacitor bank	49	0	0	0	49
conductor	1707	0	5	0	1712
fuse	36	0	0	0	36
lightning arrestor	20	0	0	0	20
switch	8	0	2	0	10
transformer	60	2	3	0	65
other	59	1	1	0	61
N.A.	32	0	1	465	498
Totals	1971	3	12	465	2451

Table 3.5. Ignition Events by Voltage of Equipment. The table shows the proportion of ignition events either in the distribution sections (left) or transmission sections (right) of the power grid. Adapted from Pacific Gas & Electric Company (2019g).

Voltage (V)	
$\leq$ 750	0.174
4,000	0.002
12,000	0.461
17,000	0.020
21,000	0.118
Distribution (other)	0.176

Voltage (V)	
60,000	0.014
70,000	0.008
115,000	0.013
230,000	0.002
Transmission (other)	0.011

Table 3.6. Ignition Events by Wire-Down Incident. The table shows the proportion of ignition events where a wire down incident occurred. Adapted from Pacific Gas & Electric Company (2019g).

Yes	0.080
No	0.733
N.A.	0.187

Table 3.7. Ignition Events by Weather Warning. The table shows the proportion of ignition events where a fire weather warning was present. Adapted from Pacific Gas & Electric Company (2019g).

Yes	0.478
No	0.113
N.A.	0.410

The final burned area of an ignition may depends on how it was sparked. Table 3.8 shows the relative proportion of distribution voltages responsible for fires of different sizes. For example, of the largest fires (larger than 5,000 acres) caused by distribution circuits, all were ignited on distribution lines carrying 12,000 Volts.

Table 3.8. Distribution Voltage Associated with Fire Size. The table shows the number of ignition events started at a particular voltage (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Voltage	**≤750**	**4,000**	**12,000**	**17,000**	**21,000**	**Distribution (other)**	Total
structure only	23	2	31	3	9	4	72
1 meter - < 3 meters	162	2	274	9	54	100	601
3 meters - 0.25 acres						168	168
< 0.25 acres	201	1	543	18	143	9	915
0.25 - 10 acres	35	1	223	16	68	107	450
10 - 100 acres	4		37	2	14	15	72
100+ acres						2	2
100 - 299 acres			7		1		8
300 - 999 acres	1		4		1		6
1,000 - 4,999 acres	1		2				3
> 5,000 acres			8				8
N.A.						18	18
Total	427	6	1129	48	290	423	2323

Table 3.9 shows similar results for transmission lines.

Table 3.9. Transmission Voltage Associated with Fire Size. The table shows the number of ignition events started at a particular voltage (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Voltage	**60,000**	**70,000**	**115,000**	**230,000**	**Transmission (other)**	Total
structure only		1			1	2
1 meter - < 3 meters	1	1	3		4	9
3 meters - 0.25 acres					2	2
< 0.25 acres	11	9	13	4		37
0.25 - 10 acres	17	5	11		5	38
10 - 100 acres	4	3	5	1	2	15
100+ acres					1	1
100 - 299 acres						
300 - 999 acres	1	1				2
1,000 - 4,999 acres			1			1
> 5,000 acres	1					1
N.A.					12	12
Total	35	20	33	5	27	120

Table 3.10 shows that, regardless of fire size, overhead equipment is the most prevalent kind of equipment for ignitions, which is the primary risk concern for PSPS events. In most cases, conductors or capacitors were the source of ignitions, although for the largest fires it is unknown (Table 3.11).

Table 3.10. Structure Type Associated with Fire Size. The table shows the number of ignition events started on a particular structure type (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Structure Type	**Overhead**	**Padmounted**	**Subsurface**	**N.A.**	Total
structure only	66		3	5	74
1 meter - < 3 meters	502	2	2	104	610
3 meters - 0.25 acres				170	170
< 0.25 acres	937	1	5	9	952
0.25 - 10 acres	374		2	112	488
10 - 100 acres	70			17	87
100+ acres				3	3
100 - 299 acres	8				8
300 - 999 acres	8				8
1,000 - 4,999 acres	4				4
> 5000 acres	2			7	9
N.A.				30	30
Total	1971	3	12	457	2443

Table 3.11. Equipment Type Associated with Fire Size. The table shows the number of ignition events started on a particular structure type (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Equipment Type	**capacitor bank**	**conductor**	**fuse**	**lightning arrestor**	**switch**	**transformer**	**other**	**N.A.**	Total
structure only		61	1		2	5		5	74
1 meter - < 3 meters	21	415	12	7	3	28	14	110	610
3 meters - 0.25 acres								170	170
< 0.25 acres	22	810	17	9	4	21	41	28	952
0.25 - 10 acres	6	337	6	4	1	9	5	120	488
10 - 100 acres		68				2		17	87
100+ acres								3	3
100 - 299 acres		8							8
300 - 999 acres		8							8
1,000 - 4,999 acres		3					1		4
> 5,000 acres		2						7	9
N.A.								30	30
Total	49	1712	36	20	10	65	61	490	2443

The final burned area may also depend on how easily the fire is able to spread. Most mid- to large-size fires were ignited near vegetation, while smaller fires ignited around other materials (Table 3.12).

Table 3.12. Ignition Materials Associated with Fire Size. The table shows the number of ignition events started by a particular material (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Material at Origin	**Vegetation**	**Building**	**Other**	**N.A.**	Total
structure only	3	42	24	5	74
1 meter - < 3 meters	500		6	104	610
3 meters - 0.25 acres				170	170
< 0.25 acres	937	1	5	9	952
0.25 - 10 acres	375	1		112	488
10 - 100 acres	69		1	17	87
100+ acres				3	3
100 - 299 acres	8				8
300 - 999 acres	8				8
1,000 - 4,999 acres	4				4
> 5,000 acres	2			7	9
N.A.				30	30
Total	1906	44	36	457	2443

Similarly, most mid- to large-size fires were ignited in rural areas, while smaller fires were often ignited in urban areas (Table 3.13). Weather warnings, which are related to wind and temperature, were often not present during past ignition events (Table 3.14). In fact, they were rarely present for fires smaller than 5,000 acres.

Table 3.13. Land Use Associated with Fire Size. The table shows the number of ignition events that occurred in rural or urban areas (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Land Use	**Rural**	**Urban**	**N.A.**	Total
structure only	25	44	5	74
1 meter - < 3 meters	339	167	104	610
3 meters - 0.25 acres			170	170
< 0.25 acres	755	188	9	952
0.25 - 10 acres	349	27	112	488
10 - 100 acres	69	1	17	87
100+ acres			3	3
100 - 299 acres	8			8
300 - 999 acres	8			8
1000 - 4999 acres	4			4
> 5000 acres	2		7	9
N.A.			30	30
Total	1559	427	457	2443

Table 3.14. Weather Warning Associated with Fire Size. The table shows the number of ignition events started with a fire weather warning present (column) for the given fire size (row). Blank entries represent zeroes. Adapted from Pacific Gas & Electric Company (2019g).

Weather Warning	**Yes**	**No**	**N.A.**	Total
structure only	4	65	5	74
1 meter - < 3 meters	34	472	104	610
3 meters - 0.25 acres			170	170
< 0.25 acres	96	847	9	952
0.25 - 10 acres	47	329	112	488
10 - 100 acres	7	63	17	87
100+ acres			3	3
100 - 299 acres		8		8
300 - 999 acres	1	7		8
1000 - 4999 acres	1	3		4
> 5000 acres	7	2		9
N.A.			30	30
Total	197	1796	450	2443

Once a fire has started and been detected, several agencies could lead the suppression efforts (Figure 3.15). For fires larger than 0.25 acres, a state or local fire agency always manages fire suppression. For smaller fires, although fire agencies handle the majority of cases, it is also possible for other organizations to be involved.

Table 3.15. Fire Suppression. The table shows the proportion of ignition events suppressed by different entities. Adapted from Pacific Gas & Electric Company (2019g).

Fire Agency	0.646
N.A.	0.292
Utility: PG&E	0.012
Customer	0.030
Self Extinguished	0.020

3.2.3 Ignition Probabilities

One way PG&E quantifies wildfire risk for overhead transmission lines is using a likelihood of ignition (Pacific Gas & Electric Company 2019a). The probabilities are provided at approximately 30,000 points along the transmission grid, which represent transmission poles carrying high-voltage lines (Pacific Gas & Electric Company 2019a). Data is only provided for a subset of transmission poles in the power grid, primarily for those that are within Tier 2 or Tier 3 zones (Figure 3.15). The distribution of ignition probabilities is shown in Figure 3.16. There are low and high probabilities both inside and outside of the HFTD.

This data is the product of a Bayesian model that considers the age of the structure, type of material, location, loading, corrosion, and other characteristics of transmission poles to create a failure curve (Thalman 2020). This curve considers failures that result in ignitions at certain wind speeds. The ignition probability values in Figures 3.15 and 3.16 represent a single point along this failure curve at 80 mph winds (Thalman 2020). Based on information in the 2019 PSPS reports, 80 mph winds are rare within PG&E's service territory and are much stronger than the wind forecasts that may trigger a PSPS event (Pacific Gas & Electric Company 2019e). Typically, forecasted sustained winds of 20-30 mph and gusts of 35-45 mph are enough to consider holding a power shutoff event (Pacific Gas & Electric Company 2019e). Observed wind speeds during an event tend to range from 30-60 mph. Only two of the eight shutoff events in 2019 observed winds over 70 mph (Pacific Gas & Electric Company 2019e).

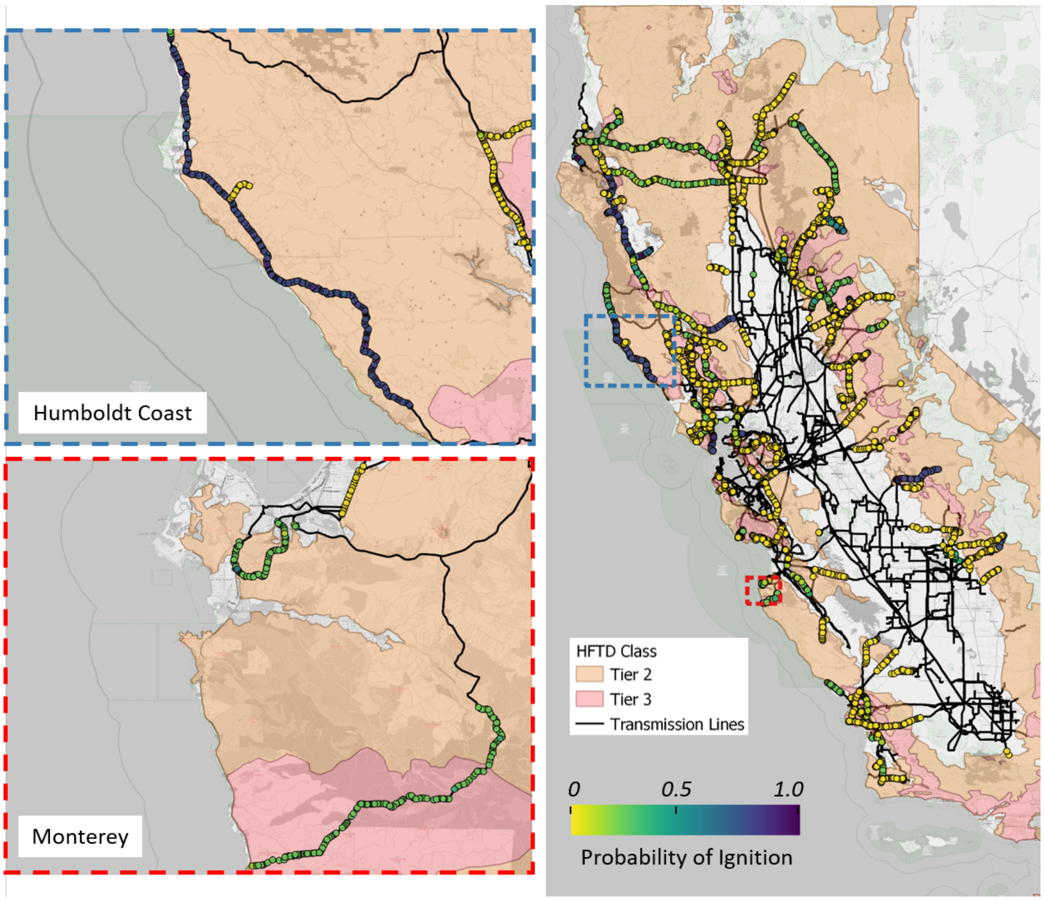

Figure 3.15. Ignition Risk on Transmission Lines. The map shows the probability of ignition (over a year), given that 80 mph wind gusts are present at points along transmission lines. Each of these points represents a utility pole carrying a high-voltage line and is colored based on the likelihood of ignition. The Monterey area (bottom left) has spans of transmission that have low probability of ignition; this can be considered a low-risk area for starting wildfires. The Humboldt coast area (top left) has spans of transmission that have high probability of ignition; this can be considered a high-risk area for starting wildfires. Adapted from Pacific Gas & Electric Company (2019a) and California Public Utilities Commission (2020).

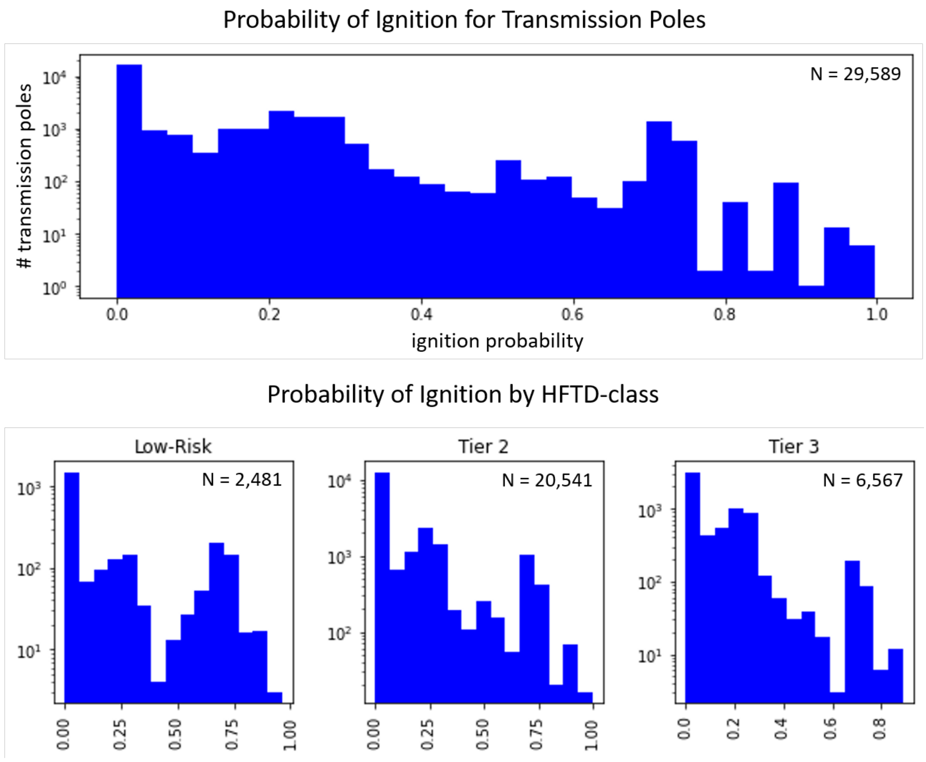

Figure 3.16. Distribution of Ignition Probabilities. These histograms show the probability of ignition on transmission poles for all poles (top) and by HFTD-class (bottom). The horizontal axis shows the likelihood and the vertical axis shows the number of poles. The total number of poles considered in each histogram is shown in the top right of the given plot. Adapted from Pacific Gas & Electric Company (2019a) and California Public Utilities Commission (2020).

3.2.4 Weather

Weather plays a large role not in only in determining when to hold a PSPS, but also in identifying high-risk areas for future planning. PG&E utilizes weather stations across the service territory to monitor wind speeds that could pose a threat to electric equipment or heighten wildfire risk (Figure 3.17). When a weather station detects winds above a certain threshold speed, it triggers a wind alert system. This alerts PG&E decision-makers to areas that should be closely monitored for more severe weather.

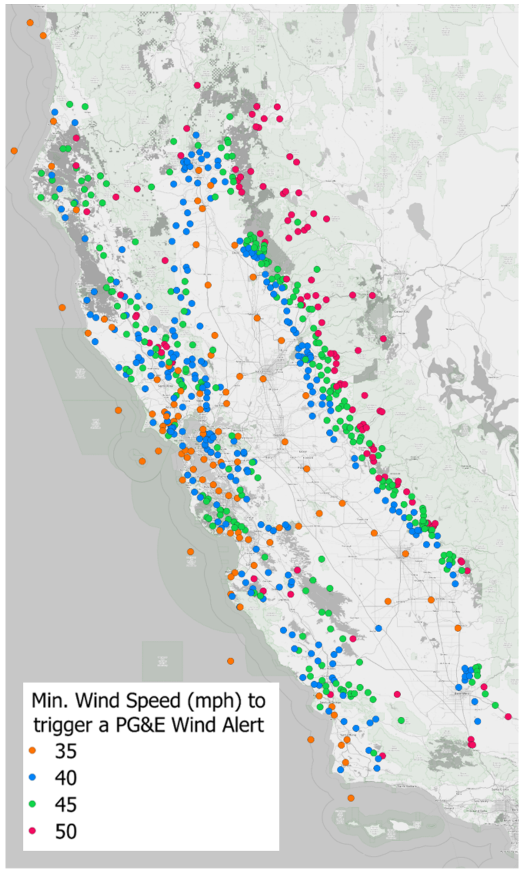

Figure 3.17. PG&E Wind Speed Thresholds. PG&E utilizes weather stations across the state to monitor wind speeds. Each point on the map is a weather station that can measure wind speeds. When gusts above a certain speed are present at a station, a wind alert is triggered for the utility company. The thresholds for alerts are rule-based, determined based on the elevation of the weather station. Each point is colored according to the minimum wind speed (mph) for triggering an alert. Adapted from Pacific Gas & Electric Company (2019i).

A RFW present in a county, issued by the NWS, can used as one of the deciding factors for considering a PSPS event. Historical data indicates that some counties are more prone to RFW than others (Figure 3.18).

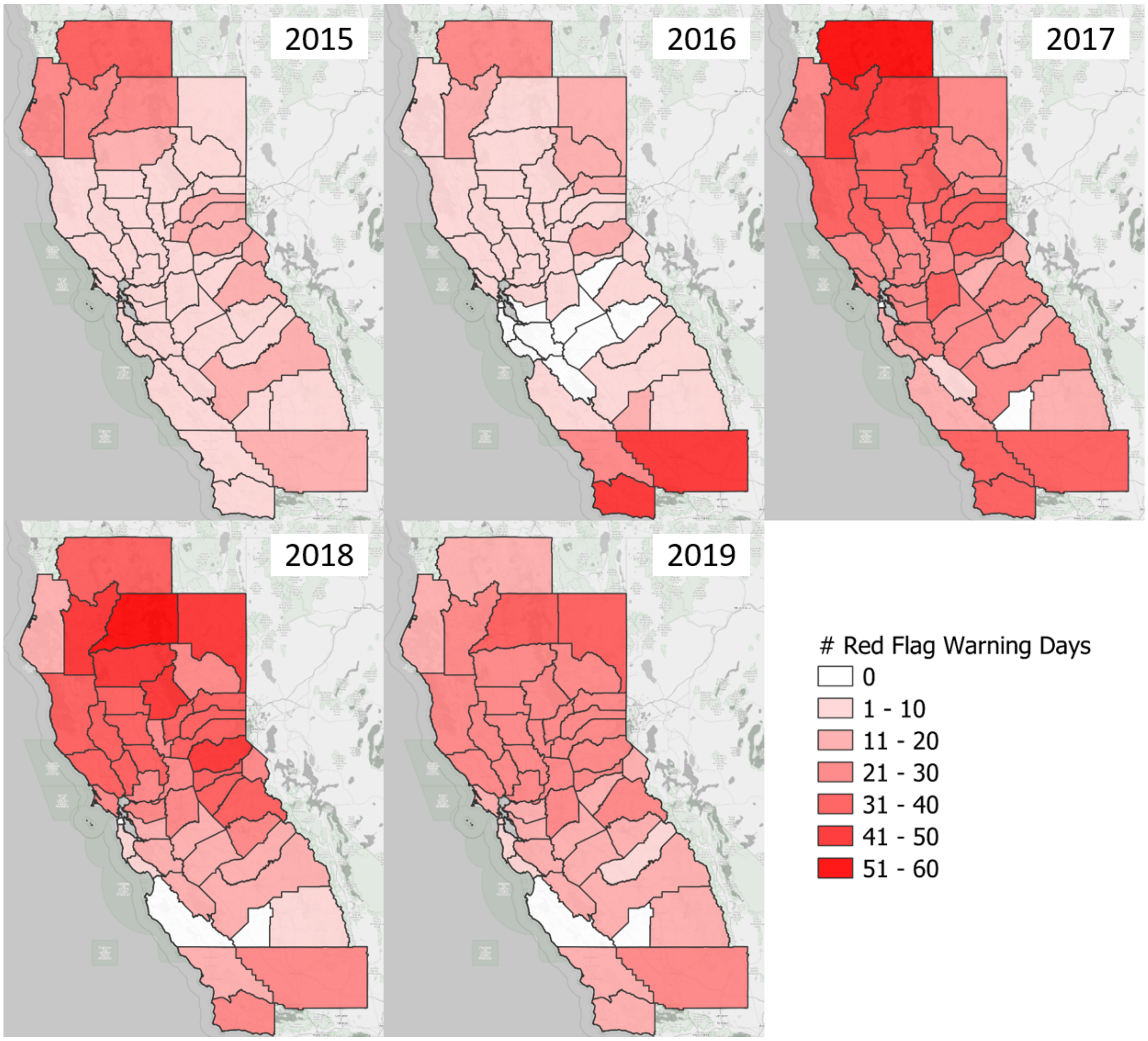

Figure 3.18. Red Flag Warnings. The maps show California's counties shaded by the number of Red Flag Warnings that occurred in a given county in a given year. The counties with the most RFW days each year were Siskiyou (2015), Kern (2016), Siskiyou (2017), Shasta (2018), and Shasta (2019). Adapted from Pacific Gas & Electric Company (2019f).

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3.2.5 PSPS Events

Every PSPS is unique. The regions affected, lines de-energized, and number of customers involved can all vary (Table 3.16). Of the eight shutoff events in 2019, we observe the following:

- the minimum duration was 16 hours,
- the minimum number of de-energized distribution lines was 17,
- the minimum number of de-energized transmission lines was 7,
- there were at minimum 11,609 total customers affected, and
- there were at minimum 173,816 customer-hours of outage.

In seven of the eight PSPS events, PG&E de-energized lines in the Sierra Foothills area.

Table 3.16. Summary of 2019 PSPS Events. This table describes each PSPS event over the course of 2019. The *Areas Affected* follows the naming convention used in the PSPS reports to the CPUC. Data on customers is calculated from the number PG&E service points on a particular circuit. Adapted from Pacific Gas & Electric Company (2020a).

Event	Area Affected	Approx. Duration (hours)	# Lines De-energized		Total Customers	Customer-Hours
			Distribution	Transmission		
Jun. 8 - 9	North Bay, Sierra Foothills	36	22	8	22,467	369,186
Sep. 23 - 24	North Bay, Sierra Foothills	47	18	10	21,720	502,185
Sep. 25 - 26	North Bay, Sierra Foothills	32	44	13	49,100	813,841
Oct. 5 - 6	Sierra Foothills	16	17	7	11,609	173,816
Oct. 9 - 12	Central Coast, East Bay, North Bay, Sacramento	90	424	79	673,024	32,910,701
Oct. 23 - 25	Bay Area, North Bay, Sierra Foothills	52	140	26	172,644	5,361,908
Oct. 26 - Nov. 1	North Bay, Sierra Foothills, Santa Cruz Mountains, North Coast, Humboldt	128	641	31	876,696	66,178,520
Nov. 20 - 21	North Bay, Napa Valley, Sierra Foothills, Shasta	39	57	7	49,202	1,373,290

Once lines are de-energized, the duration of the outage can vary widely, as shown in Figure 3.19. Differences in duration occur not only across different events, but also across circuits in the same event. Tier 2 and Tier 3 HFTD zones can have much longer outages compared to non-HFTD areas.

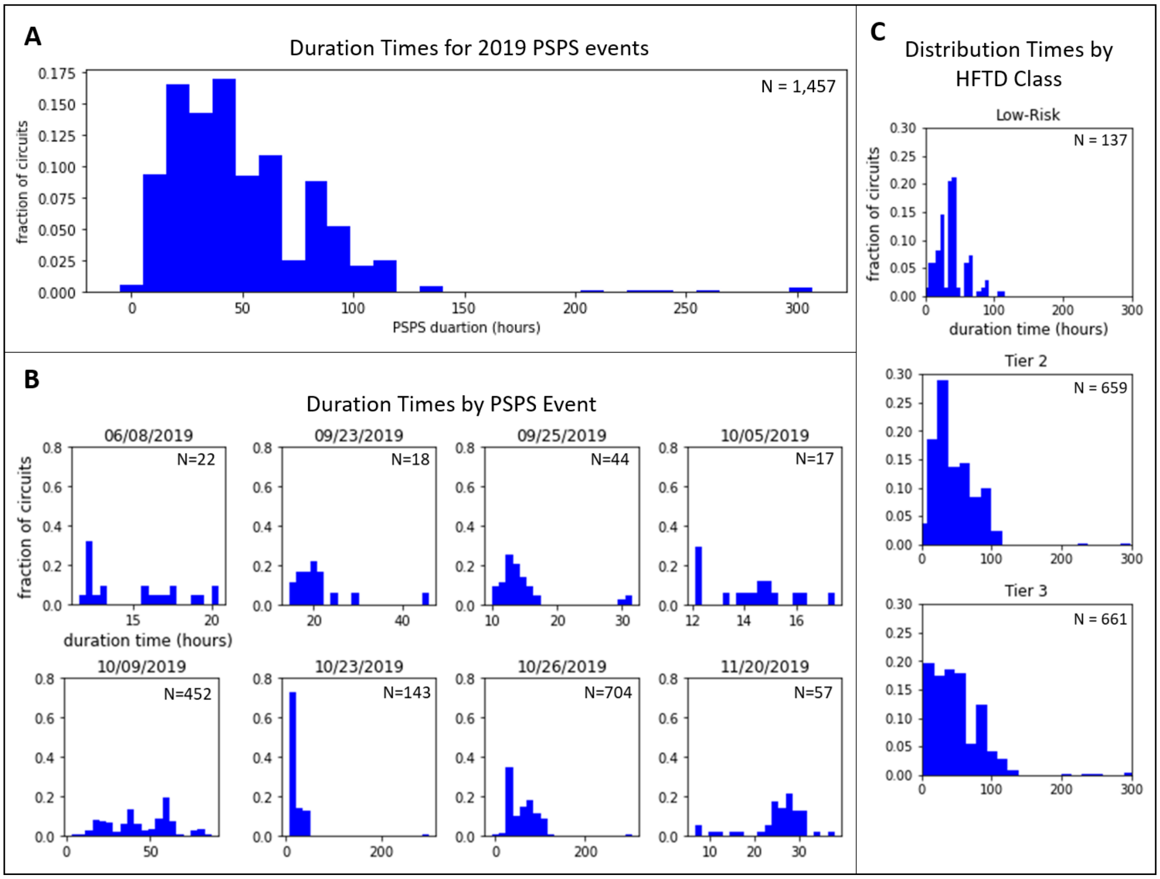


Figure 3.19. Duration of PSPS Events. These histograms show the distribution of duration times (A) for all 2019 PSPS events, (B) by PSPS event, and (C) by HFTD class. The horizontal axis shows the estimated duration time in hours, and the vertical axis shows the proportion of circuits exhibiting a given duration. The total number of circuits considered is shown as *N* in the upper right corner of each histogram. Adapted from Pacific Gas & Electric Company (2020a).

Restoration Process

We synthesize data on the power-restoration process using two sources: (1) GIS files for individual PSPS events provided in the WMP and (2) the PSPS reports to the CPUC.

The GIS files for each power shutdown contain attribute tables with information on each de-energized circuit in the given event. The relevant columns are the event start time (i.e. the date-time the circuit was de-energized), t_{start}, and the total duration of the event (i.e. the length of time the circuit was de-enegrized), Δt_{outage}. We use these two values to calculate the end time for the outage (i.e. the date-time the circuit was re-energized), t_{end}, as shown in Equation 3.1:

$$t_{start} + \Delta t_{outage} = t_{end}. \tag{3.1}$$

The post-PSPS reports to the CPUC contained information on the date-time the restoration process began for a particular PSPS event. While the GIS files provide data at the circuit level, the reports provide information at a broader geographic scale. Estimates for the start of the restoration process are given for regions or phases of the event. Many of the utility shutdowns in 2019 were conducted across different districts within the PG&E service territory and in multiple time phases. For example, the PSPS on November 20 - 21 was planned across 10 districts in 5 separate time phases (Pacific Gas & Electric Company 2019c). For each PSPS event, we chose to use the earliest time provided in the reports as the start time of the restoration process for all circuits involved in the event. To calculate the duration of the restoration process, t_{rest} for each circuit, Δt_{rest}, we used the estimated start time of restoration and the previously calculated end time of the event, t_{end}, as shown in Equation 3.2:

$$t_{end} - t_{rest} = \Delta t_{rest}. \tag{3.2}$$

Applying this heuristic across all PSPS events produced the distribution of restoration times shown in Figure 3.20. It is important to note there are negative values for restoration times for some power shutoffs, which is not realistic. This is a direct result of the way we chose to calculate these times; we were limited by incomplete information for multi-stage events in the reports to the CPUC. Similar to the outage duration times, the restoration times also vary greatly across events and between circuits in the same event. Tier 2 and Tier 3 HFTD zones may take much longer to restore power to compared to non-HFTD areas.

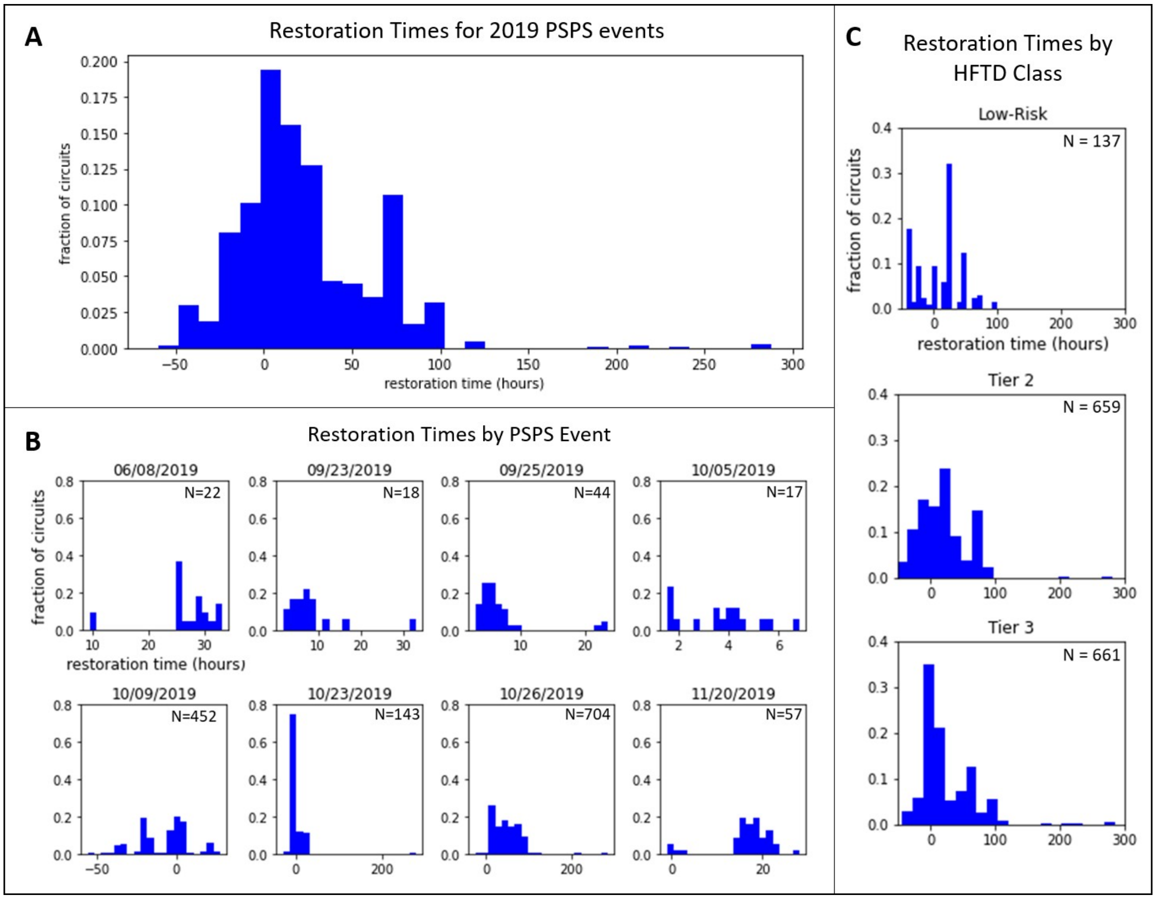


Figure 3.20. Restoration Duration for PSPS Events. These histograms show the distribution for the calculated restoration times (A) for all 2019 PSPS events, (B) by PSPS event, and (C) by HFTD class. The horizontal axis shows the estimated restoration time in hours, and the vertical axis shows the proportion of circuits exhibiting a given duration. The total number of circuits considered is shown as *N* in the upper right corner of each histogram. Adapted from Pacific Gas & Electric Company (2020a).

PSPS Impact

The impact of PSPS events can be viewed and measured from three different perspectives: (1) customers affected, (2) economic cost, and (3) wildfire risk reduction.

PG&E has two metrics for the impact of PSPS events on utility customers: (1) the total number of customer service points and (2) the total customer-hours of power outage, both provided at the individual circuit level.

In addition to reporting the total number of customer service points on de-energized distribution circuits, PG&E breaks this figure down by customer type (Table 3.17). Customers can be residential, medical baseline, commercial industrial, or not fall into any of these categories (other). Each of these groups of customers can present a different kind of economic or social loss for the utility company and the community when a power shutdown occurs.

Table 3.17. Number of De-energized Customers for 2019 PSPS Events. PG&E counts customers as the number of service points on a distribution circuit. The table shows the proportion of each type of customer and the total customers for the PSPS. Adapted from Pacific Gas & Electric Company (2020a).

	# Customers				
	Residential	Medical Baseline	Commercial Industrial	Other	Total
Jun. 8 - 9	0.82	0.07	0.11	0.01	24,038
Sep. 23 - 24	0.85	0.06	0.07	0.01	23,146
Sep. 25 - 26	0.84	0.06	0.10	0.001	52,084
Oct. 5 - 6	0.83	0.06	0.10	0.01	12,339
Oct. 9 - 12	0.86	0.04	0.10	0.01	765,706
Oct. 23 - 25	0.85	0.04	0.10	0.01	186,748
Oct. 26 - Nov. 1	0.85	> 0.01	0.10	0.01	1,003,657
Nov. 20 - 21	0.82	0.05	0.10	0.03	51,634

The customer-hours of outage, C_H, is the product of the number of customers without power, N, and the PSPS duration, Δt_{outage}, as shown in Equation 3.3. The distribution of customer-hours for each event is given by Equation 3.3:

$$N * \Delta t_{outage} = C_H \tag{3.3}$$

and shown in Figure 3.21.

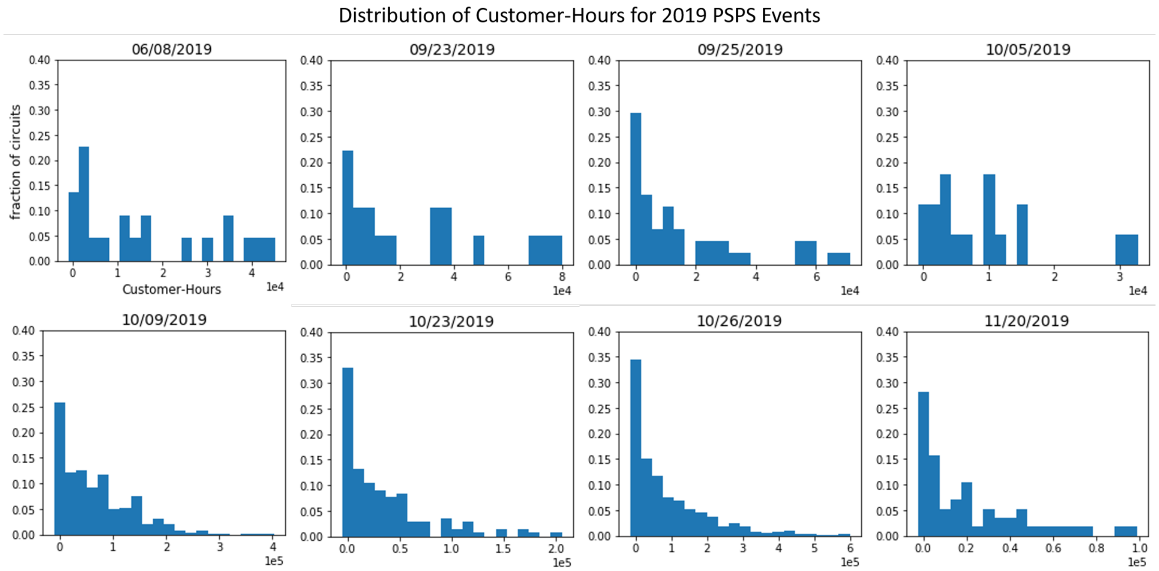


Figure 3.21. Customer-Hours of Outage. These histograms show the distribution for the calculated customer-hours of outage by PSPS event. The horizontal axis shows the customer-hours and the vertical axis shows the proportion of circuits exhibiting a given value. Adapted from Pacific Gas & Electric Company (2020a).

Figure 3.22 shows each of these three variables as map layers. The duration map (Hours of Outage) and customer map (Customers on Circuit) can be overlaid to create the customer-hours map. Customer-hours serves as a more descriptive impact measure than either of its component layers, but all three are needed to understand the outcome. To illustrate this, we compare the first two power shutdowns in 2019, on June 8-9 and September 23-25. Both events were executed in the same geographic areas and comparable distribution and transmission assets were de-energized—22 and 18 distribution circuits, and 8 and 10 transmission lines, respectively for the June and September events. Although the September outage lasted approximately 11 hours longer than the June outage, the June outage affected approximately 750 more customers than the September outage. Overall, the later PSPS event exceeded the earlier event by approximately 13,000 customer-hours, or a factor of 1.4. From only the duration statistics, we would conclude that the September outage was a larger disruption; from only the customer statistics, we would conclude that the June outage was the larger disruption; from only the customer-hours statistics, we would conclude that the September outage was the larger disruption. However, when we look at all three, the answer is not as clear and can be subjective.

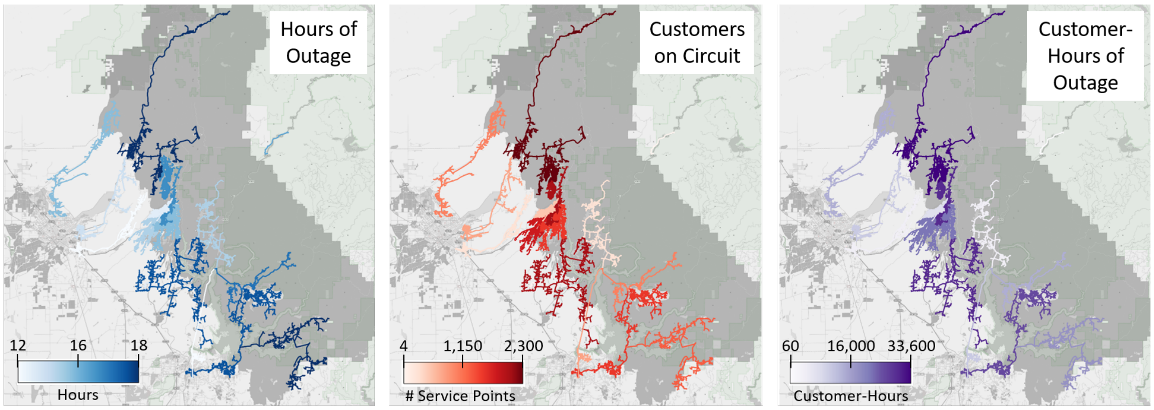


Figure 3.22. Customer-Hours Map. Impact measures for the Nov. 20 – 21 power shutoff are shown for de-energized circuits. The customer-hours of outage (right) is a product of the total hours of outage for each circuit (left) and the total number of customers (middle). Adapted from Pacific Gas & Electric Company (2020a).

In addition the direct impact on utility customers, power shutoff events have economic implications for both customers and electric power providers. During a PSPS event, there is the potential for electric power demand to fall below supply— this lost load has an associated economic cost. A power outage is also potentially time when a customer is paying for a service they are not receiving, or when the utility company is absorbing the cost of this.

We conduct a similar analysis to Wolfram (2019). In Figure 3.23, we estimate the megawatts (MWs) of lost load during a PSPS by comparing power usage in California during a 2019 shutoff event and during the corresponding time frame in 2018. We looked at the week of October 7 (Monday) to October 12 (Sunday) in 2019 and October 8 (Monday) to October 13 (Sunday) in 2018. PG&E held a PSPS event starting October 9 and ending October 12 (2019). We did not identify any large power outages that occurred in the corresponding week in 2018. During the PSPS event, the MWs of power delivered in 2018 exceeds that of 2019 (Figure 3.23). Before and after the outage begins, there is either a comparable load delivered between the two years, or 2019 demand exceeds 2018 demand (Figure 3.23). A similar trend was observed when conducting this analysis for all 2019 PSPS events.

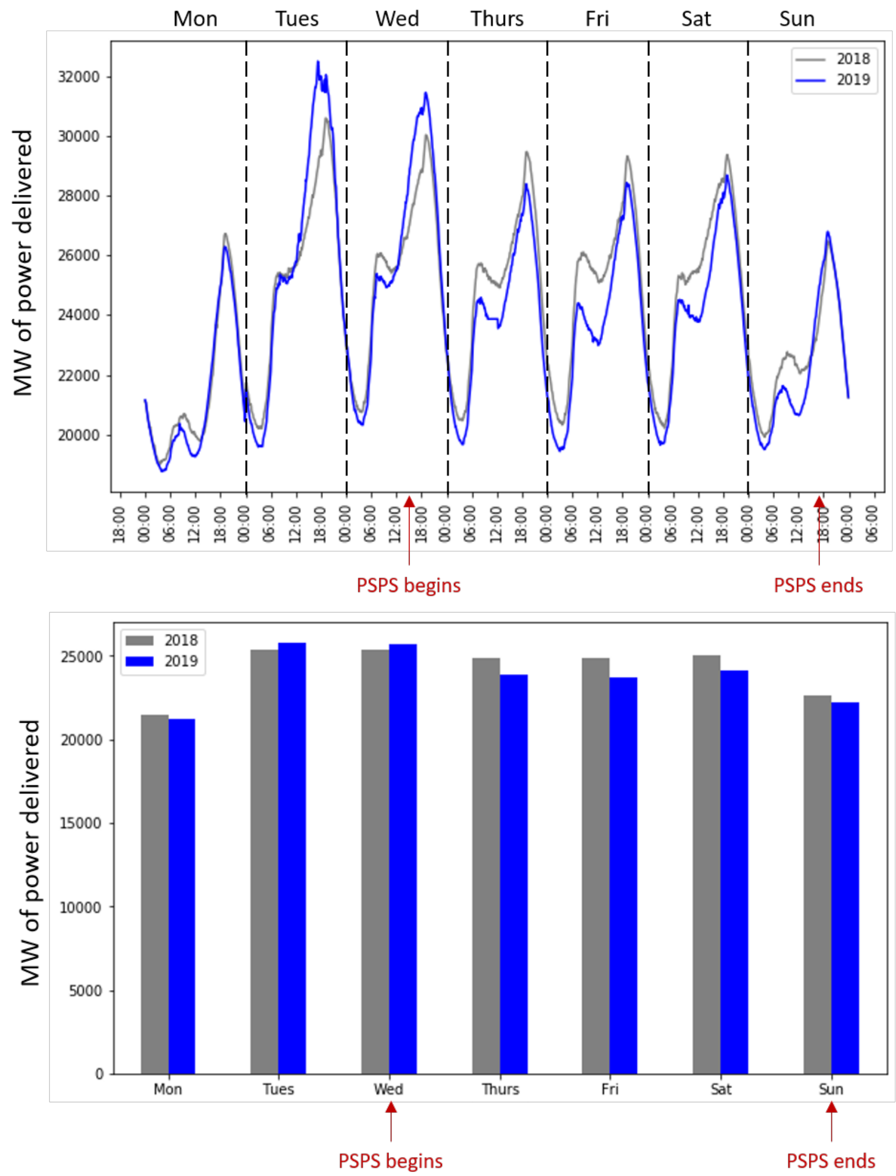


Figure 3.23. Lost Load During a PSPS. The time series plot (top) shows the MWs of electric power delivered at 5-minute intervals in parts of the state covered by the CAISO. The bar chart (bottom) shows the average instantaneous MWs of power delivered for each day of a PSPS. Lines/bars in blue reflect demand during the week of a PSPS event in 2019, and lines/bars in gray reflect demand for the corresponding week in 2018. The data reflects the Oct. 9 - Oct. 12 PSPS event. Adapted from California Independent System Operator (2020).

One of the key decisions utility operators must make when considering a PSPS is where to shut off power. De-energizing lines in a particular area significantly decreases the chance of an ignition occurring, but energized portions of the electric grid are still at risk. Thus, ignitions can and have occurred during past PSPS events. Table 3.18 shows the counts and fire sizes of ignition events that occurred in the same time frame as the 2019 PSPS events.

Table 3.18. Ignitions Occurring During PSPS Events. The table shows the number of utility-caused ignitions that sparked during a PSPS event anywhere in the utility service territory, along with largest size of resulting fires. Adapted from Pacific Gas & Electric Company (2019g) and Pacific Gas & Electric Company (2019a).

PSPS Event	# Ignitions	Size
Jun. 8 - 9	11	≤ 0.25 acres
Sep. 23 - 24	5	≤ 10 acres
Sep. 25 - 26	5	≤ 10 acres
Oct. 5 - 6	3	≤ 10 acres
Oct. 9 - 12	8	≤ 10 acres
Oct. 23 - 25	6	≤ 10 acres
Oct. 26 - Nov. 1	46	< 100 acres
Nov. 20 - 21	3	≤ 10 acres

Figure 3.24 shows the location of ignitions for the September 25 shutoff event. For this particular event, some of the ignitions occurred relatively near the areas that were targeted for de-energization, while others occurred in areas that were not considered. All of the ignitions that occurred during this event were outside of the HFTD.

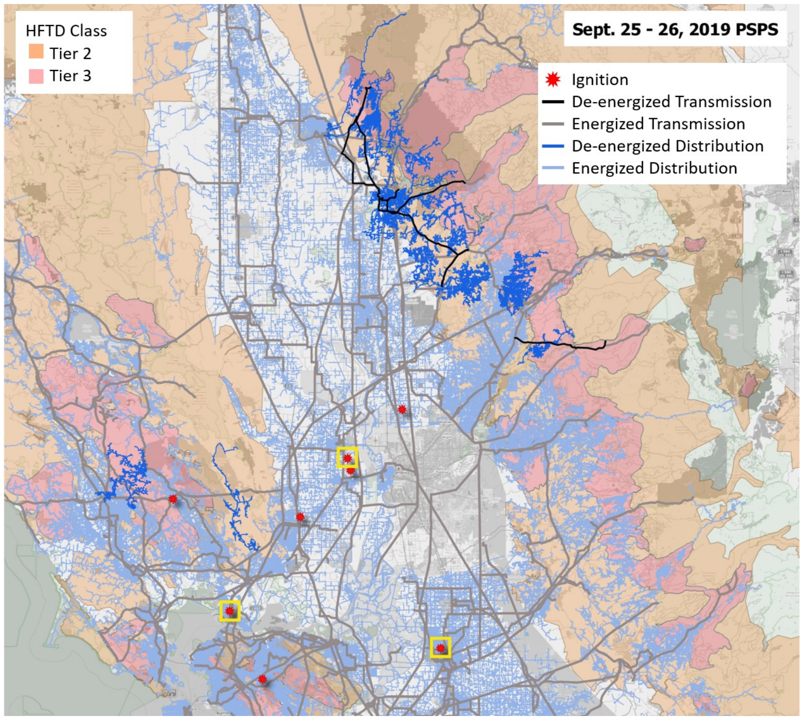


Figure 3.24. Ignition Sites During a PSPS. This figure shows eight ignition sites that occurred during the September 25 shutoff event. The ignitions boxed in yellow resulted in the largest fires among the eight. PG&E classifies these in the size range from 0.25 acres to 10 acres. Adapted from Pacific Gas & Electric Company (2019g) and Pacific Gas & Electric Company (2019a).

3.3 Discussion

We gain several insights from this exploratory data analysis.

Overhead power lines are the main source of wildfire risk in the electric power grid. Risk can vary greatly between individual assets in the both the transmission and distribution grid based on geographic location, vegetation management, and equipment condition.

Utility-caused ignitions commonly occur on distribution lines in rural areas with vegetation near the sight of ignition. Ignitions are most often caused by contact from foreign objects or equipment failure. Many other factors can be associated with utility-caused ignitions, including geographic location, voltage, outages, and equipment type. Although most ignitions result in fires that burn less than 0.25 acres, they have the potential to grow larger than

5,000 acres.

Past PSPS events can vary widely in scope in terms of duration, restoration times, number of customers affected, and lost electric load. Many of the key decisions in executing a power shutoff involve meteorological data on wind and humidity.

The descriptive analysis in this chapter sets the stage for another kind of model: predictive. We can use the data described—on ignitions, weather, the electric power grid, and past power shutoffs— to determine the decision factors that will be important for future PSPS events.

CHAPTER 4:
Further Analysis

This chapter explores methods to analyze the characteristics of de-energized circuits, the fire size of an ignition, and the social cost of PSPS events.

4.1 Characteristics of De-energization

In this section, we build three models— logistic regression, classification tree, and random forest— to answer two questions. Given that critical PSPS weather conditions are present in an area can we

1. Identify important variables that determine which circuits are shut off?
2. Predict which circuits are shut off?

The answer to the first question provides insight into PG&E's decision-making process. In this thesis, we assume that the data PG&E provides (such as that in Chapter 3) serves a role in the planning and execution of a power shutoff. Aside from weather conditions, we do not have the details of how PG&E uses information relating to terrain or the properties of the power grid. Building regression and classification models allows us to identify important variables. The second question allows us to validate the results of the first question by "recreating" past PSPS events. This analysis is conducted using the R Programming Language (R Core Team 2020) using the `glm`, `rpart`, and `randomForest` libraries.

4.1.1 Data Description

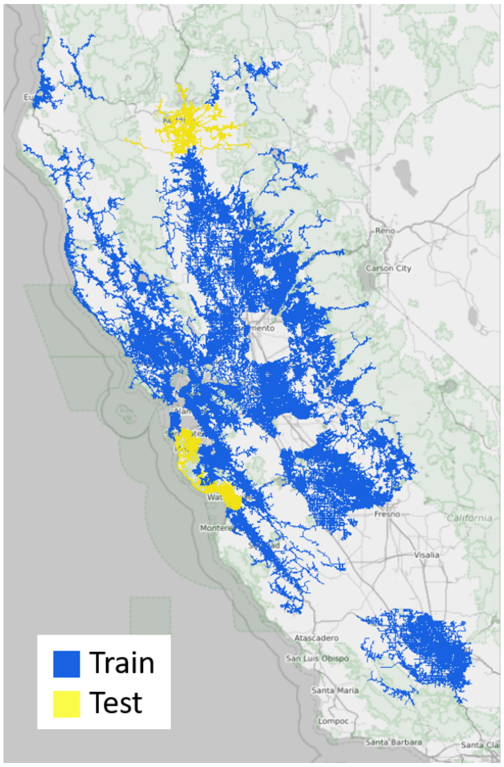
For this analysis, we combined data on the electric distribution grid (see Section 3.2.1) and on past PSPS events (see Section 3.2.5). We subset this data to include circuits within 41 (of 47) of PG&E's administrative districts. These districts were chosen such that at least one circuit within the district had been part of a PSPS event in 2019.The intent is to ensure that we are not including areas that had never been considered for a power shutoff and are unlikely to be considered for one in the future.

The metadata on distributions circuits consists of 14 explanatory variables on line-mileage, reliability measures, vegetation, and risk scores. We omit the following:

- Location variables: These variables indicate the region, division, and district that each circuit falls within. For this analysis, we chose to focus on variables that are inherent properties of the distribution lines. Including location variables was also likely to skew our results because some districts experience multiple PSPS events in 2019, and thus appear significantly more often than others;
- Redundant variables: Several of the line-mileage variables were linearly dependent or highly correlated with each other. We chose to only keep a subset of these variables to avoid collinearity issues;
- Variables with too many missing values: We kept only those variables that had values for at least half of all observations. We did this to ensure there would be a large enough sample size to conduct analysis on.

We reduce the predictor space to six explanatory variables: circuit risk score (numeric); total line miles (numeric); proportion of HFTD, Zone 1, Tier 2 miles, and Tier 3 miles (numeric); and whether the circuit is within the HFTD (binary). The response is a binary variable indicating whether or not a particular circuit was part at least one PSPS event in 2019.

The final subset of data covers 2,345 distribution circuits. We split this data into a train and test set consisting of approximately 90% (2,000 circuits) and 10% (189 circuits) of the data, respectively (Figure 4.1). For the test set, we hold out three districts (Peninsula, Coast, and Redding) where three separate PSPS events had occurred.



	In a PSPS?		
	TRUE	FALSE	*Total*
Train	26%	74%	*2246*
Test	37%	63%	*189*

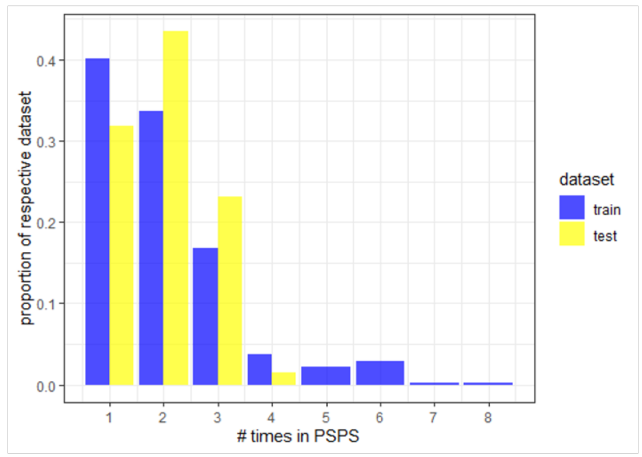


Figure 4.1. Train/Test Data Split. This figure shows the breakdown between train and test set for the de-energization characteristics analysis. Information on the train and test sets is shown in blue and yellow, respectively.

4.1.2 Logistic Regression

A logistic regression is in the form of

$$p = \frac{e^{\eta}}{1 + e^{\eta}} \tag{4.1}$$

where η is a linear combination of predictors, x_i, such that

$$\eta = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n. \tag{4.2}$$

For our analysis, the response variable, p, represents the likelihood that a particular circuit will be de-energized during a PSPS event. As an example a circuit with $p = 0.95$ is very likely to be de-energized, while $p = 0.05$ is very unlikely to be de-energized.

We tried over 20 models and considered second-order polynomial terms for all numeric variables and all two-way interactions between variables. In the model building process, we utilized step-wise regression in the backward and forward direction, along with Akaike information criterion (AIC) and Bayesian information criterion (BIC) to select variables.

To select the best model we calculate the ten-fold cross validated error on the training set for each candidate model. We use a weighted error function (Equation 4.3) with a range of weights (w_0 and w_1) and a range for threshold probabilities (θ) for classification.

$$\varepsilon = \frac{1}{N}\sum_{i=1}^{N} w_0(y_i == 0)(\hat{p}_i \geq \theta) + w_1(y_i == 1)(\hat{p}_i < \theta) \tag{4.3}$$

Here, ϵ is the cross-validated error, N is the number of observations/circuits, y indicates whether a circuit was on ($y == 0$) or off ($y == 1$) during a PSPS, and $\hat{p}$ is the probability the circuit is turned off (output from logistic regression). The first term in the summation represents a false positive— we classify the circuit as de-energized, but it was left on during the actual PSPS. The second term in the summation represents a false negative— we classify the circuit as energized, but it was turned off during the actual PSPS.

We use a range of values for $\theta \in [0, 1]$ in increments of 0.05, and we use three sets of weights — $\{w_0 = w_1 = 0.5\}$, $\{w_0 = 0.75, w_1 = 0.25\}$, and $\{w_0 = 0.25, w1 = 0.75\}$ — to represent tradeoffs between the false positive and false negative rate. If a utility company is willing to take on a higher false positive rate, then we consider them to take a more conservative approach to power shutoffs— they tend to de-energize more circuits than necessary to reduce wildfire risk.

As the best model, we chose the model that had the minimum cross-validated error in the 0.4 to 0.6 range for θ for all three sets of weights. The model took the form of

$$\eta = -4.5 + 0.13x_1 - 0.006x_2 + 2.19\{x_3 == 1\} \tag{4.4}$$

where x_1 is the circuit risk score, x_2 is the total line-mileage, and $x_3 == 1$ indicates the circuit is within the HFTD.

Figures 4.2 and 4.3 show the performance of the best model on the test set.

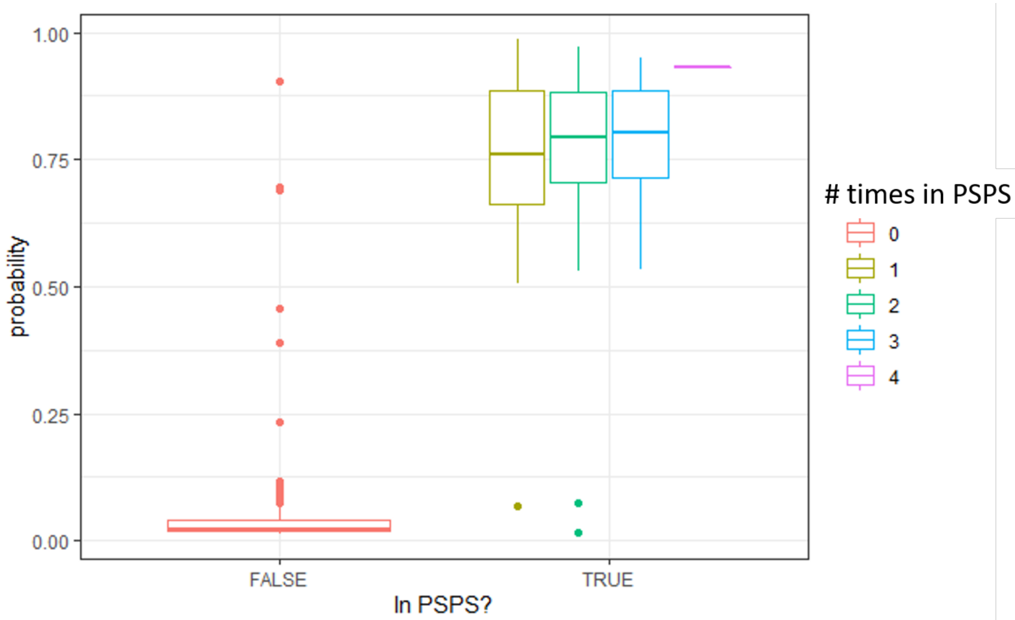


Figure 4.2. Boxplot of Logistic Regression Prediction. The plot shows the distribution of predicted probabilities (vertical axis) for the true class of circuits (horizontal axis). The plot also differentiates between circuits that experienced PSPS events 0, 1, or ≥ 1 times by color.

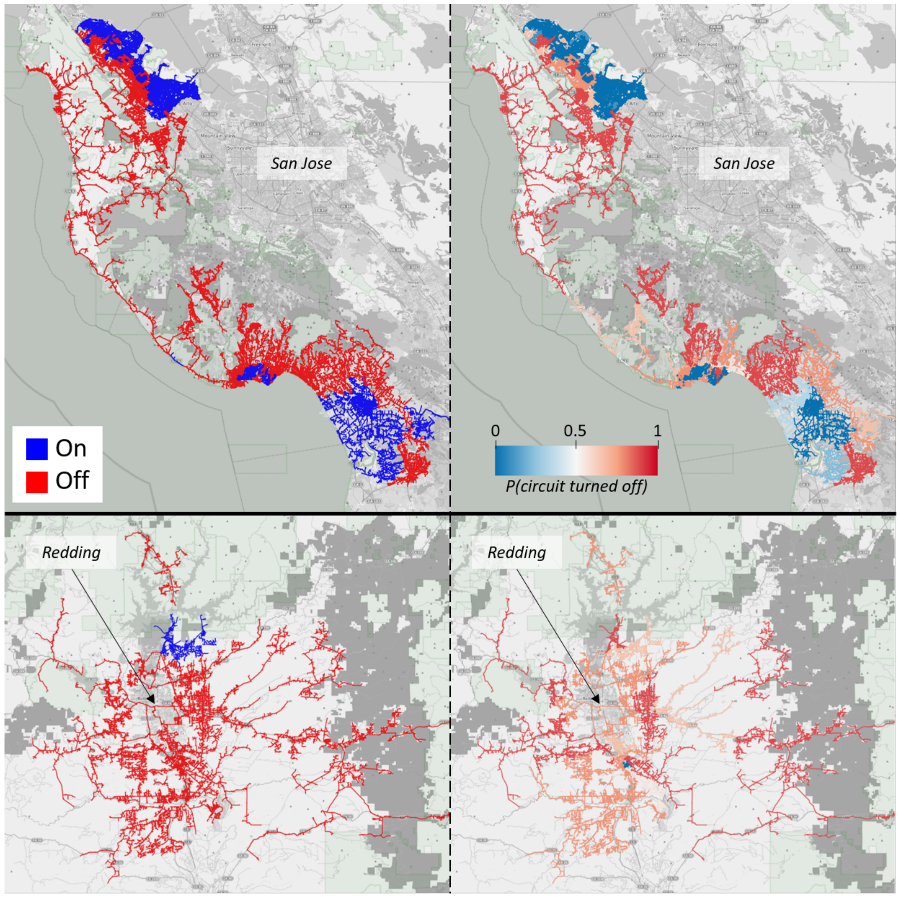


Figure 4.3. Map of Logistic Regression Prediction. The left side shows which circuits were de-energized in a PSPS (red), and the right side shows the same circuits shaded by their likelihood to be shut off as predicted by the logistic regression. The Peninsula and Coast districts are shown on top, and the Redding district is shown on the bottom.

4.1.3 Classification Tree

We build a classification/decision tree that, similar to the logistic regression, outputs p, the likelihood that a particular circuit will be de-energized during a PSPS event. Using the training set we use the Gini impurity index to grow the tree, and we prune the tree to one standard error above the minimum classification error. The final tree is shown in Figure 4.4. Figures 4.5 and 4.6 show the predictive performance of the classification tree on the test set.

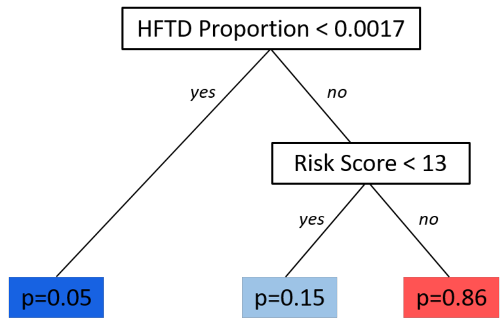


Figure 4.4. Classification Tree. The two variables that are split on are: (1) the proportion of total miles that fall within the HFTD and (2) the PG&E risk score. The leaves show p, the probability of a circuit that falls within that category is de-energized during a PSPS event.

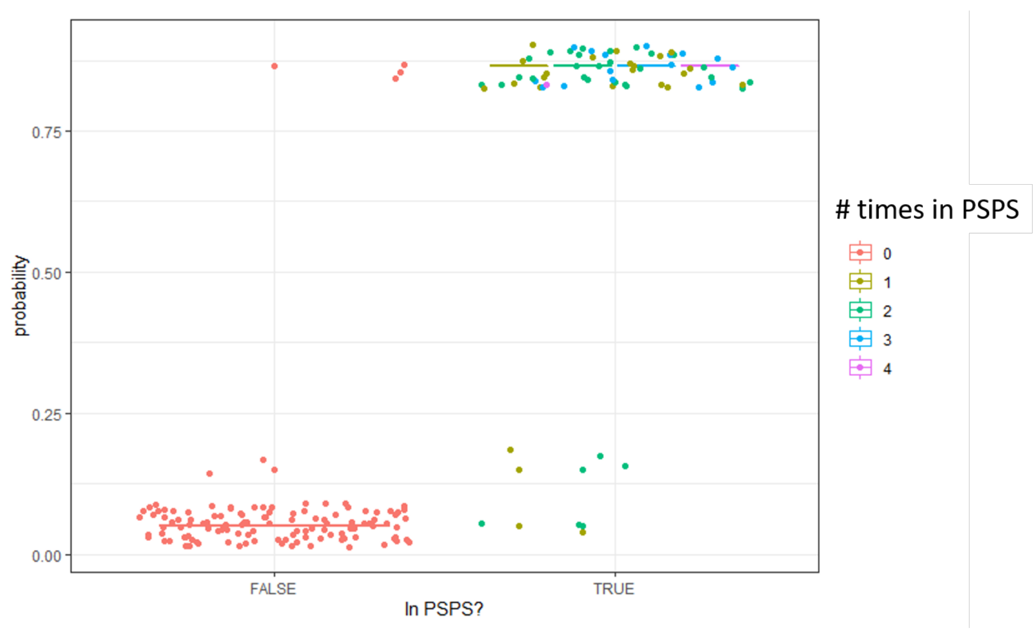


Figure 4.5. Boxplot of Classification Tree Prediction. The plot shows the distribution of predicted probabilities (vertical axis) for the true class of circuits (horizontal axis). The plot also differentiates between circuits that experienced PSPS events 0, 1, or ≥ 1 times by color.

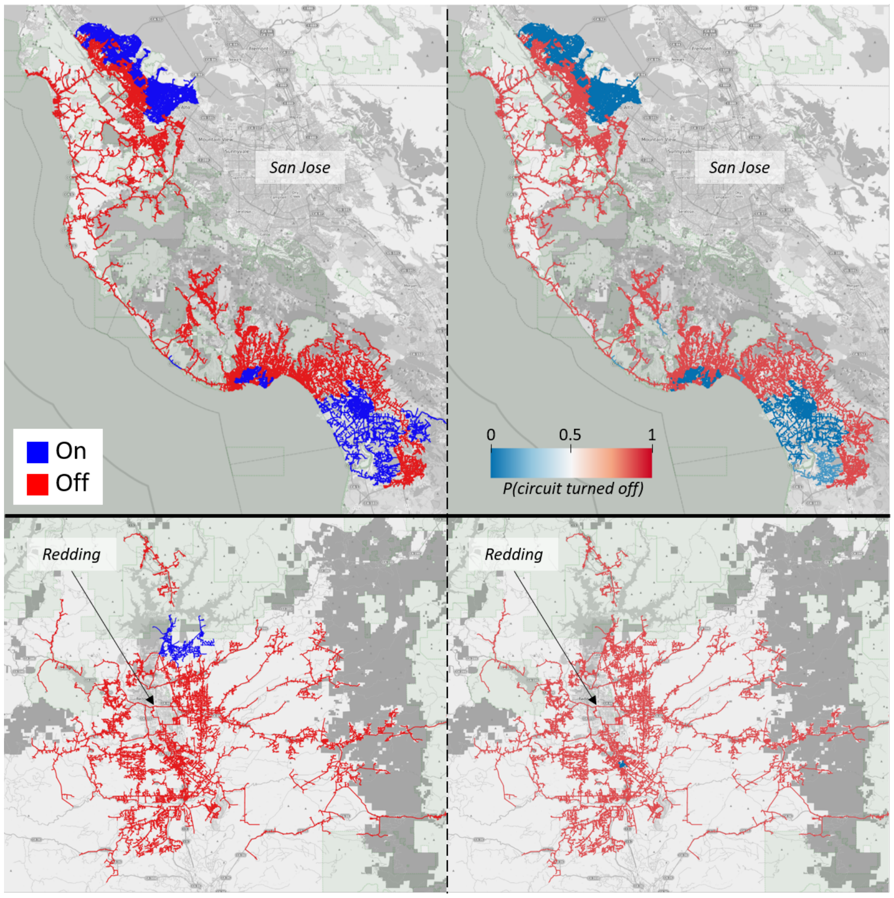


Figure 4.6. Map of Classification Tree Prediction. The left side shows which circuits were de-energized in a PSPS (red), and the right side shows the same circuits shaded by their likelihood to be shut off as predicted by the classification tree. The Peninsula and Coast districts are shown on top, and the Redding district is shown on the bottom.

4.1.4 Random Forest

We build a RF that outputs p, the likelihood that a particular circuit will be de-energized during a PSPS event. The RF is built by calculating the out-of-bag error values. We build 200 trees that each split on two randomly chosen variables. The variable importance for the RF is shown in Figure 4.7. Figures 4.8 and 4.9 show the predictive performance of the RF on the test set.

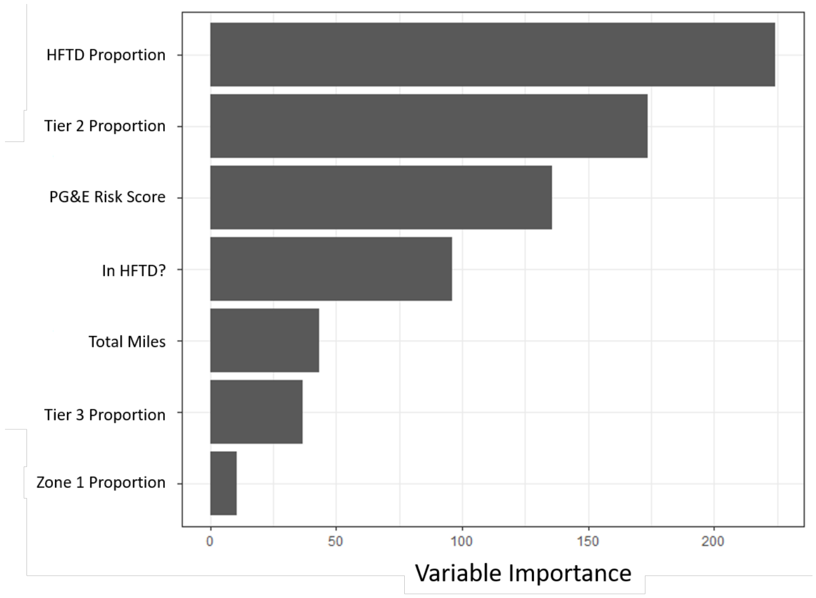


Figure 4.7. Variable Importance for Random Forest. Variable importance (horizontal axis) is measured as the mean decrease in node impurity.

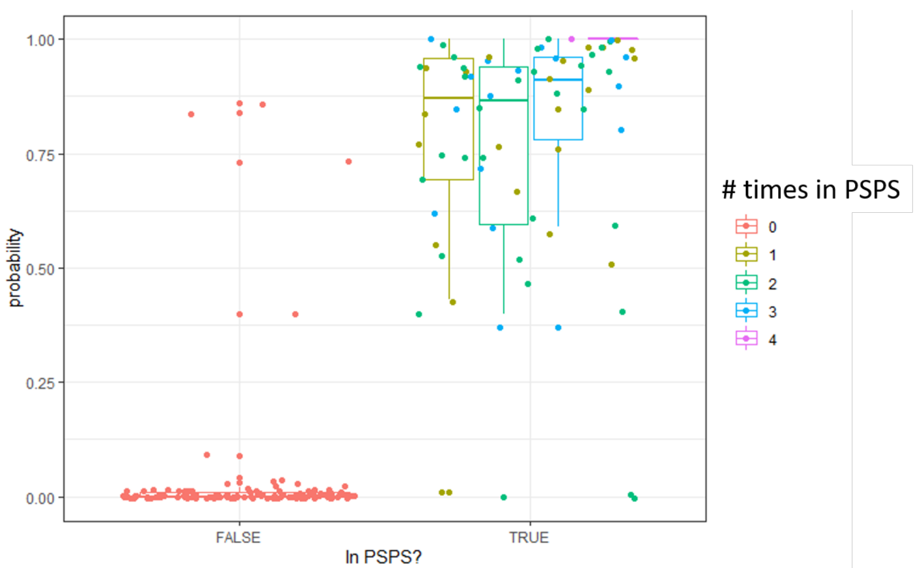


Figure 4.8. Boxplot of Random Forest Prediction. The plot shows the distribution of predicted probabilities (vertical axis) for the true class of circuits (horizontal axis). The plot also differentiates between circuits that experienced PSPS events 0, 1, or ≥ 1 times by color.

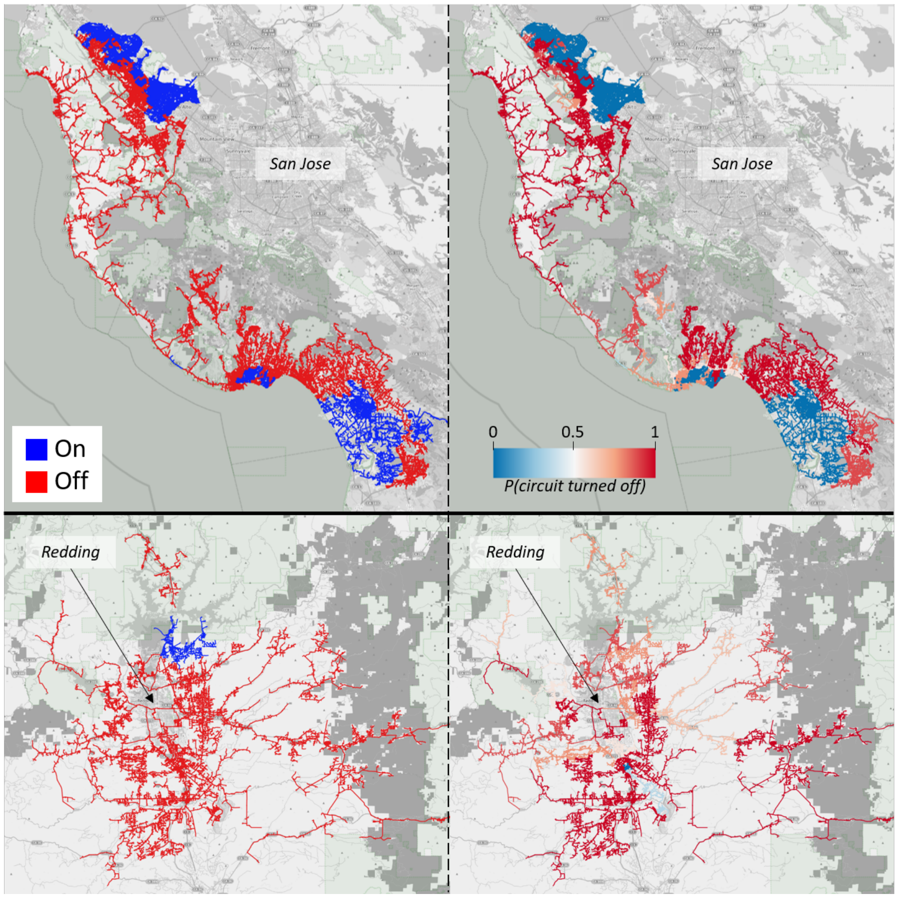


Figure 4.9. Map of Random Forest Prediction. The left side shows which circuits were de-energized in a PSPS (red), and the right side shows the same circuits shaded by their likelihood to be shut off as predicted by the random forest. The Peninsula and Coast districts are shown on top, and the Redding district is shown on the bottom.

4.1.5 Comparison of Methods

We compare the performance of the three models— logistic regression, classification tree, and RF— in a receiver operating characteristic (ROC) curve (Figure 4.10). This plot shows the ability of a binary classifier to discriminate between classes as its threshold classification probability is varied. Using the area under the curve (AUC) metric, we observe that all three models have similar performance. The AUC is 0.974, 0.965, and 0.970 for the logistic, tree, and RF models, respectively.

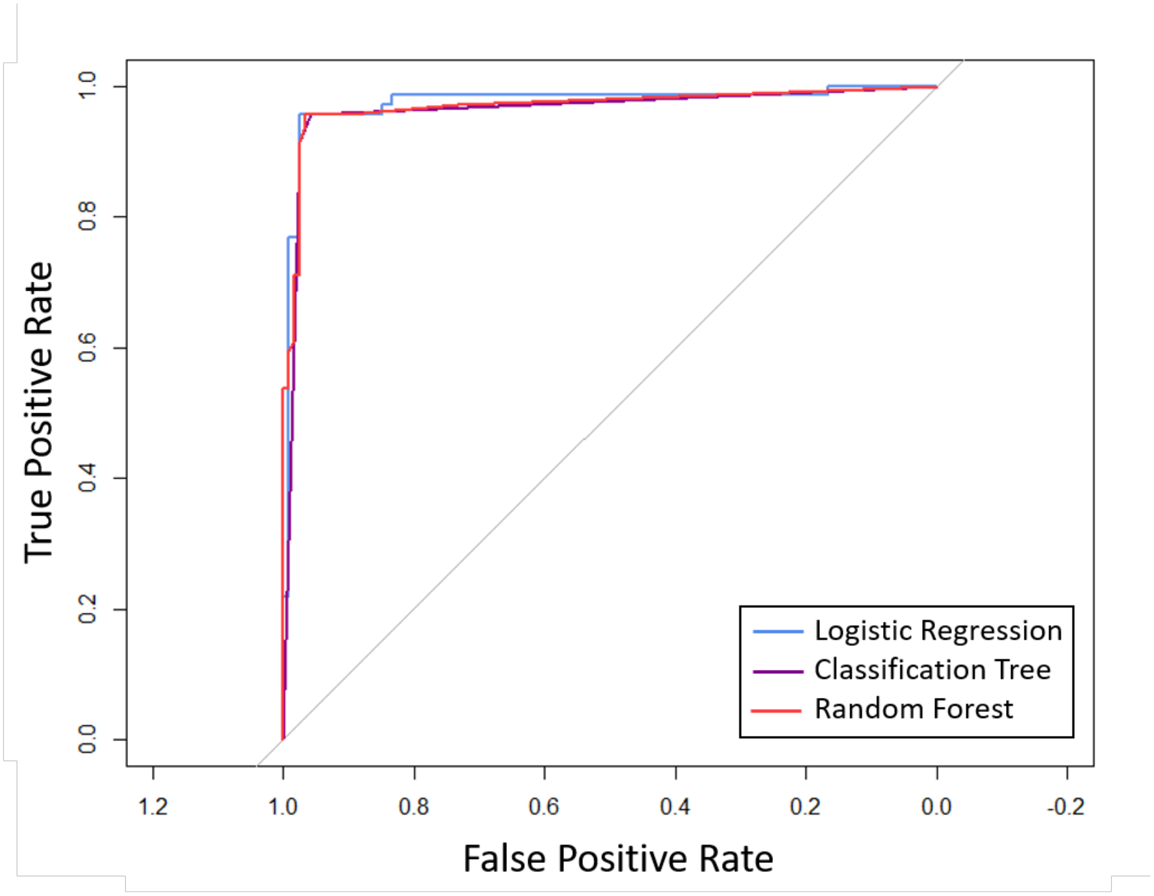


Figure 4.10. Receiver Operating Characteristic Curve. This plot compares the three modeling methods. All have similar performance based the area under the curve.

Across all three models, variables relating to the HFTD are important in predicting the likelihood of a circuit to be de-energized. More specifically, the binary HFTD variable is a linear predictor in the logistic regression; the proportion of HFTD miles is a decision-split for the classification tree; and the HFTD and Tier 2 proportions are the two most important variables in the RF. The PG&E risk score is also influential in all three models.

4.2 Predicting Fire Size from Ignitions

For this analysis, we use the ignition data set described in Section 3.2.2. Our goal is to conduct a similar analysis to Cortez and Morais (2007) to predict the size of a fire caused by a utility-ignition. Because the ignition data set provides the fire size as a categorical, rather than a numeric variable, we build a classification tree and RF. However, these methods are unsuccessful. Given the large amount of missing data and the unbalanced number of observations within each fire size category (Figure 3.13), we are unable to build a useful classifier. Based on the past research on wildfire modeling (Section 2.3.1) and this attempt at an analysis, we would require a greater amount and potentially a different type of data to conduct an analysis that would yield insightful results.

4.3 Estimating the Cost of a PSPS

Chapter 3 discusses the impact of a PSPS event in terms of the duration of an outage, the number of customers without power, and the lost electric load. The next step is to ask: what does this translate to in economic or social costs?

There is a vast literature on how to estimate the value of “lost” power during an electric utility outage, but there is no single answer or method (U.S. Department of Energy 2017). It is a challenging problem because not only are electric power consumption patterns complex, but so are the human interactions that occur during outages (Sullivan et al. 2018). Building an economic model to calculate the cost of power outages requires considering a number of factors: the duration of an outage; the residential load; the small and large business load; geographic location; how consumption varies based on weather, type of customer, time of year, or time of day; and how prepared customers are for outages (e.g. advanced notification, backup generators) (U.S. Department of Energy 2017).

In this section, we combine the results from large scale outage-cost studies, such as those considered in Sullivan et al. (2018), and the data from 2019 PSPS events to provide an estimate of the economic cost of each of these events. Our simple method provides a baseline for understanding the socioeconomic losses associated with PG&E’s intentional power shutoffs and how they compare to those of wildfires.

4.3.1 Method

We consider three values: (1) customer-hours of outage, (2) average electric consumption, and (3) cost per unserved Kilowatt-hour (kWh).

We refer to customer-hours of outage as C_H. This data is available for each PSPS event for both residential and commercial/industrial customers in Pacific Gas & Electric Company (2020a). This metric is discussed in more detail in Section 3.2.5. We do not consider customers that fall into the customer-class "other" as defined by PG&E.

We refer to average electric power consumption per customer per hour in Kilowatts (kWs) as R. For this analysis we use a value of 0.77 kW per customer per hour, which is provided in Rockzsffore and Zafar (2015) as the average electricity usage for residential customers. Because electric usage varies widely for commercial/industrial customers, we could not find an average usage figure. Thus we assume all types of customers have the same consumption rate and use our calculation as a lower-bound estimate.

We refer to cost per unserved kWh as K_U. This is defined as the "cost for an outage event normalized by the amount of unserved energy" (Sullivan et al. 2018). We use the online Interruption Cost Estimate (ICE) Calculator, developed by Sullivan et al. (2018) to obtain values for residential and commercial/industrial customers, which are \$20.77 per kWh and \$47.01 per kWh for residential and commercial/industrial customers, respectively.

We combine these values to calculate the estimated cost of a PSPS event (Equation 4.5), considering residential and customer/industrial customers separately.

$$C_H * R * K_U = \text{total cost} \tag{4.5}$$

4.3.2 Results

Using this method, we estimate the total cost for each event, shown in Table 4.1. The total cost ranges from tens of millions of dollars for the smaller PSPS events to billions of dollars for the larger PSPS events. These estimates are consistent with those reported in the media (e.g., *Reuters* 2019; *CNBC* 2019; *Wall Street Journal, The* 2019).

Table 4.2 shows the average cost of a PSPS event to individual customers who experienced a power outage. This cost varies by the total number of customers affected and the duration of the outage. For example, the Oct. 26-Nov. 1 event, was the largest power shutoff in terms of cost and it has the highest per customer cost for both residential and commercial/industrial

Table 4.1. Estimated Cost of PSPS Events. The table shows the estimated cost for each 2019 PSPS event, broken down by residential and customer/industrial customers.

Event	Residential ($)	Commercial/Industrial ($)	Total ($)
Jun. 8-9	5,137,623	13,786,296	18,923,919
Sep. 23-24	7,189,034	14,427,454	21,616,488
Sep. 25-26	11,519,963	26,990,202	38,510,165
Oct. 5-6	2,423,518	6,665,294	9,088,812
Oct. 9-12	487,446,183	1,339,121,713	1,826,567,896
Oct. 23-25	77,149,567	194,077,916	271,227,483
Oct. 26-Nov. 1	993,325,420	2,721,792,525	3,715,117,945
Nov. 20-21	18,621,660	53,640,822	72,262,482

customers. The per customer cost for each PSPS event can be interpreted as the dollar amount a customer should be willing to pay to avoid the outage event (Wolfram 2019).

Table 4.2. Average PSPS Cost per Customer. The table shows the estimated cost per customer for each 2019 PSPS event, broken down by each customer type.

	Cost ($) per Customer	
Event	Residential	Commercial/Industrial
Jun. 8-9	261.52	5,385.27
Sep. 23-24	363.49	8,383.18
Sep. 25-26	263.49	5,412.11
Oct. 5-6	236.44	5,182.97
Oct. 9-12	752.63	17,159.43
Oct. 23-25	485.83	10,703.02
Oct. 26-Nov. 1	1,161.71	26,643.23
Nov. 20-21	438.64	9,916.96

Would a customer be willing to pay hundreds or thousands of dollars to avoid the impact of a PSPS event? As a basis for comparison, we consider other relative costs that customers typically face. Some PG&E customers may choose to invest in a generator; this would allow a household (or business) to operate under normal conditions during a power shutoff. However, the cost of an average household generator can range from hundreds to thousands of dollars. In practice, many customers choose to invest only in basic emergency supplies, such as flashlights, batteries, and handheld generators, to mitigate the consequences of a power outage. The cost of a PSPS event can also be compared to the cost of past wildfires and wildfire suppression efforts. The wildfire known as the Camp Fire that occurred in 2018 is estimated to have cost between $1.4 billion to at least $2 billion (Feo et al. 2020). Additionally, CAL FIRE has spent an estimated $2 billion per year since 2018 on wildfire suppression efforts. Our total estimated cost for all 2019 PSPS events is approximately $5 billion (Feo et al. 2020).

4.4 Discussion

The three analyses in this chapter reveal several insights on the tensions in PSPS events.

Simple regression models can help us understand what future PSPS events may look like. Choosing which circuits to de-energized in a region is largely determined by the characteristics of the terrain around power lines. The proportion of line-miles in the HFTD is an important factor in all three models we build.

Understanding and predicting the dynamics of wildfires caused by utility-ignitions is not a simple task. It requires vast amount of detailed data. If PG&E is collecting this kind of data, it is not publicly available.

Finally, PSPS events present enormous costs to customers, utility companies, and the state as a whole. This cost can vary widely across power shutoff events.

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CHAPTER 5:
Summary and Conclusions

We conclude with a summary of contributions and results, as well as the potential for future work.

5.1 Summary

This thesis performs three modeling and analysis tasks: (1) we conduct an extensive exploratory data analysis on the PG&E power grid, utility-caused ignitions, and past PSPS events; (2) we develop models to gain insight on the PG&E decision process during PSPS events; and (3) using power outage studies and economic models, we estimate the social cost of PSPS events.

This thesis curates, integrates, and visualizes data from a wide variety of sources, including PG&E, the CPUC, and the CAISO. This allows us to identify interactions between the electric power grid, terrain, climate, and wildfire risk. We learn that ignition risk varies widely across the power grid, and that utility-caused ignitions are common and have the potential to grow into large fires. Additionally, PSPS events can vary largely in scope based on duration, the number of customers affected, and the lost electric load. Much of the data we use is part of a yearly effort put out by PG&E in their WMP; new data will be available in 2021 that may supplement this analysis and provide more information on the state of the power grid.

Furthermore, we develop simple regression models to determine important factors in PG&E's decision making-process when executing PSPS events. We observe the key drivers to be whether or not a circuit crosses the HFTD (and what proportion of it is within this area) and the PG&E risk score. We would benefit from having more complete and detailed data for all assets in the power grid to conduct a more thorough analysis.

Finally, we translate concrete impact measures such as the duration, customers, and lost load during a power shutoff into the overall social cost of PSPS events. We determine that for past events, this value ranges from tens of millions to potentially billions of dollars. We estimate a lower bound for this cost that does not consider the varying electric demand of commercial and/or industrial customers or customers PG&E classifies as “other” or “medical baseline.”

5.2 Conclusions

In this thesis we set out to answer three questions.

1. Under what conditions should the power be shut down?
2. Where should the power be shut down and for how long?
3. When and how should the power be restored?

We conclude the following with our various modeling and analysis tasks.

1. The primary driver for PSPS events is weather, and more specifically, high-speed winds. These wind events create stress on structures within the power grid that result in failures and ignition events.
2. The location and duration for a PSPS event depends on where critical weather event occurs and how long it lasts. The conditions of electric utility assets also play a key role—equipment that is aged, in need of vegetation maintenance, or in an area that has high potential for fire spread has a higher likelihood of being de-energized during a PSPS.
3. The restoration process begins to occur once wind speeds have fallen below a certain threshold and is forecasted to continue decreasing. The duration of this process largely depends on the total line miles that need to be patrolled, if the line miles can be accessed aerially or via ground crews, and the failures/disruptions that need to be addressed.

5.3 Future Work

The next phase in this research should consider a higher level of fidelity in modeling wildfires, the electric power grid, and the cost of power outages. This thesis takes a descriptive and predictive approach, and building on this, future work should take on a prescriptive approach. This would entail formulating an optimization problem that examines tradeoffs in the timing, scope, and duration of PSPS events. As discussed in detail in Section 2.4, the preliminary work of Rhodes et al. (2020) takes a first step at constructing an optimization model, but it is missing many of the details we have determined to be important in PSPS modeling.

Additionally, PG&E's decision-making process and risk analysis (and that of other utility companies) is evolving as more PSPS events take place. They have ongoing efforts to improve risk analysis, and they have partnered with academic institutions and other commercial entities. One of these, Technosylva, "provides advanced GIS-enabled software solutions for wildfire protection planning, operational response & firefighter and public safety" (Technosylva 2020).

Finally, the results from analyses in this field have implications for Department of Defense (DOD) operations. Some military installations in the U.S. are exposed to wildfire risk, and all are vulnerable to power outages. The DOD would greatly benefit from better understanding the interactions between wildfires and the electric power grid, as well as how to restore power safely and efficiently.

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