Exceedance Probabilities and Recurrence Intervals for Extended Power Outages in the United States

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List of Acronyms

CAIDI	Customer Average Interruption Duration Index
CDF	Customer Damage Function
CPUC	California Public Utilities Commission
DOE	U.S. Department of Energy
EAGLE-I	Environment for Analysis of Geo-Located Energy Information
EIA	U.S. Energy Information Administration
FEMA	Federal Emergency Management Agency
FIPS	Federal Information Processing Standards
MED	major event day
NARUC	National Association of Regulatory Utility Commissioners
NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
NYSERDA	New York State Energy Research and Development Authority
ORNL	Oak Ridge National Laboratory
PG&E	Pacific Gas & Electric Company
PNNL	Pacific Northwest National Laboratory
PSPS	public safety power shutoff
SAIDI	System Average Interruption Duration Index
SAIFI	System Average Interruption Frequency Index

Executive Summary

Power outages cause significant economic and societal impacts. An increasing likelihood of extreme weather coupled with aging grid infrastructure is leading to a higher prevalence of extended power outages, which can leave customers without power for multiple days or even weeks. Planners at the facility, local, state, and federal levels are interested in resilience solutions to reduce the impacts of extended power outages. Resilience solutions—such as installing backup systems, integrating microgrid solutions, weatherizing buildings and backup systems, and hardening distribution and transmission components—can reduce the consequences of extended power outages, but these solutions come with increased capital costs.

Conducting cost-benefit analyses is important for determining which steps to take to mitigate the impact of power outages without investing in ineffective and cost-prohibitive resilience solutions. The expected benefits of resilience investments depend on the frequency of power outages of various durations, particularly extended outages lasting several hours, days, or weeks. A significant barrier to resilience planning is the lack of publicly available data on the frequency and duration of extended power outages. The absence of outage duration information severely limits the ability to conduct quantitative cost-benefit analyses of resilience investments.

This report provides estimates of recurrence intervals and conditional exceedance probabilities for major power outages by U.S. region between 2015 and 2021. Additionally, we provide estimates for grid management, particularly outages caused by California's public safety power shutoffs (PSPS), and for natural outages caused by major hurricanes. Outage recurrence intervals are the average number of years between outage events, and conditional exceedance probabilities are the likelihoods that a customer who experiences a major power outage will experience an outage exceeding a given duration. Major outage events are those that affect 10,000 or more customers, as defined by the U.S. Department of Energy's (DOE's) *Electric Emergency Incident and Disturbance Report*, called OE-417[1] (DOE 2020). These results can be applied to determine the likelihood of experiencing long-duration outages, which can be integrated into cost-benefit analyses of resilience solutions and broader energy resilience studies.

We developed a methodology to estimate customer outage durations for extended outage events using publicly available data on customer outages. Shorter-duration power outages are relatively common, with customers experiencing on average more than one power outage each year lasting fewer than 12 hours. An outage event lasting between 1 day and 1 week is expected to occur between once every 16 years and once every 42 years, depending on the region, with an average recurrence rate of once every 32 years across the contiguous United States. Table ES-1 presents the estimated recurrence intervals.

[1] At times referred to as DOE-417.

Table ES- 1. Estimated Recurrence Intervals by Region and Outage Duration[a]

	Contiguous	Central	Eastern	Southern	Western
0–12 hours	0.8	0.9	0.9	0.7	1.0
12–24 hours	67	58	34	44	84
1–2 days	59	48	37	34	78
2–3 days	127	87	77	74	203
3–5 days	152	229	167	68	186
5–7 days	495	1,112	675	191	1,152
>1 week	790	1,316	2,517	290	1,479

[a] The values give the average number of years between outages of a given duration.

Table ES-2 summarizes the estimated exceedance probabilities. Of the customer outages caused by major outage events in the contiguous United States, we estimate that 50% exceed 12 hours, 36% exceed 24 hours, 3.5% exceed 5 days, and 1.3% exceed 1 week. These estimates vary by region, with the southern states significantly more likely to experience extended outages than other states. Among all major power outages experienced between 2015 and 2021 in the southern United States, 2.6% lasted longer than 1 week, whereas this value is less than 1% for all other regions.

Table ES- 2. Exceedance Probabilities for Major Events by Region and for Select Hazards[a]

Duration	Contiguous	Central	Eastern	Southern	Western	Hurricanes	PSPS
12 hours	50.3%	47.5%	47.8%	53.6%	44.2%	69.5%	87.3%
1 day	35.7%	32.0%	29.7%	41.2%	29.6%	52.1%	66.3%
3 days	9.9%	4.3%	4.7%	14.4%	7.2%	33.4%	13.1%
5 days	3.5%	1.4%	1.1%	5.4%	2.0%	6.5%	0.4%
7 days	1.3%	0.7%	0.2%	2.2%	0.6%	2.5%	0.0%

[a] The numbers presented are conditional probabilities given that an event occurs. Hurricane exceedance probabilities are based on the analysis of six major hurricane events, and the PSPS exceedance probabilities are based on California PSPS events from 2017 through 2021.

A key outcome of this analysis is providing a basis for estimating the frequency of outages of varying durations for resilience valuations or risk assessments. The frequency and duration of extended power outages are critical inputs in resilience planning and underpin any probabilistic approach to valuing the benefits of resilience investments. This work contributes to quantitative resilience analysis; however, there is still significant work to be done.

The estimates presented are based on a limited time series of power outages and are subject to significant uncertainty, particularly for the longer-duration outage estimates. Few outage events last more than a week, and these events often impact a large area. Access to a longer continuous data set could help corroborate or correct the estimates presented here, and more data could reduce but not eliminate uncertainty surrounding outage estimates. Future research could determine how outage durations vary by cause to better understand the relationship between underlying hazards and outage events. Further data and research could also quantify the uncertainty of estimates by determining standard errors by outage duration. Future power outages might have different characteristics than historical power outages. Additional work could model changes in underlying hazards to determine how outage frequency and duration will vary over time. Extended power outage events are inevitable, but understanding their causes, probabilities, and impacts are important steps to reducing the consequences of extended power outages through resilience-enhancing solutions.

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1 Introduction

Extended power outages cause significant economic and societal impacts. Major outage events between 2003 and 2012 resulted in an estimated average of $22 to $41 billion in damages per year (Executive Office of the President 2013), and sustained power interruptions cause an estimated $43 to $62 billion per year (Lacommare et al. 2018).[2] Increases in extreme weather events along with aging infrastructure are further increasing the prevalence and costs of extended outages (Reidmiller et al. 2018; Sanstad et al. 2020). Planners at the facility, local, state, and federal levels are interested in resilience solutions to reduce the likelihood and impacts of extended power outages (Hotchkiss and Dane 2019; National Research Council 2012).

This report provides estimates of recurrence intervals and conditional exceedance probabilities for major power outages by U.S. region between 2015 and 2021. Additionally, we provide estimates for grid management, particularly outages caused by California's public safety power shutoffs (PSPS), and for natural outages caused by major hurricanes. Outage recurrence intervals are the average number of years between outage events, whereas conditional exceedance probabilities are the likelihoods that a customer who experiences a major power outage will experience an outage exceeding a given duration. Major outage events are those that impact 10,000 or more customers, as defined by the U.S. Department of Energy's (DOE's) *Electric Emergency Incident and Disturbance Report*, called OE-417[3] (DOE 2020). These estimates can help better understand the likelihood of long-duration outage events and can be used as part of a broader cost-benefit analysis of resilience investments.

Resilience solutions—such as installing emergency backup systems, integrating microgrid solutions, weatherizing buildings, and hardening distribution and transmission components—can reduce the impact of extended power outages, but these solutions can also come with increased capital or operating costs (Consolidated Edison 2013; Zamuda et al. 2019). Decision makers have many competing demands for limited resources, meaning resilience investments are required to demonstrate "significant and measurable short and long-term benefits that balance or exceed the costs" (National Research Council 2012). Comparing the costs of installing, operating, and maintaining a resilience investment to its benefits, which include decreased outage costs, helps planners determine which resilience investments are worth implementing.[4] Cost-benefit analyses allow decision makers to compare resilience investments consistently and comprehensively (Kallay et al. 2021), and they are a requirement for many federal and state resilience grants. For example, the Federal Emergency Management Agency's (FEMA's) Hazard Mitigation Assistance grants "require that mitigation measures demonstrate cost-effectiveness" in order for applicants to be eligible for funding (FEMA 2022).

Expected risks from power outages are calculated by multiplying the consequence across potential outage events with the probability that a given disruptive event will occur. The benefits

[2] Cost estimates are converted to 2022 dollars.
[3] At times also referred to as DOE-417
[4] Many of the societal impacts of power outages that are most important to consider, such as impacts to health and quality of life, are not associated with dollar values. Decision makers should account for these nonmonetary factors alongside more easily quantifiable costs.

of resilience investments in reducing the risk of power outages therefore depend on the frequency of power outages of various durations. A significant barrier to resilience planning is the lack of publicly available data on the frequency and duration of extended power outages (Ji et al. 2016). Hanna and Marqusee (2022) state that a "lack of access to comprehensive power outage data sets…make[s] it difficult to analyze complex interactions between long-duration outages and resilience." The absence of such outage duration information severely limits the ability to conduct quantitative cost-benefit analyses of resilience solutions.

Power outage costs can vary nonlinearly with outage duration (Ericson and Lisell 2020). A report by Consolidated Edison (2013) on the value of hardening electric assets to storms notes:

> Outage duration is perhaps the single most exacerbating factor when electrical power is interrupted. In general, shorter outages, although disruptive, do not have the same degree of negative impact on quality of life and society's ability to function as do longer outages. When combined with large populations and/or dense critical infrastructure, outage durations have a multiplier effect on the magnitude of the disruption caused by the power loss.

Outage impacts during extended interruptions can increase exponentially (NARUC 2019). Damages such as food spoilage occur only after an outage exceeds a given period (Ericson and Lisell 2020). Importantly, the risk of morbidity and mortality increase with outage duration, especially during certain types of disruptive events (e.g., power outage during an extreme heat or cold event). Even when the underlying costs are relatively linear with outage duration, backup systems can prevent most damage from occurring until fuel resources are depleted (e.g., systems run out of battery charge, run out of fuel, or break down), which leads to nonlinearities. Metrics and tools used to value short-duration outages rely on average outage durations and frequency, and they are insufficient for determining the cost of extended outages and the value of resilience solutions (Murphy et al. 2020). Quantitative cost-benefit assessments of resilience solutions depend on the frequency and duration of extended power outages (NYSERDA 2014; Willis and Kia 2015), and they can depend particularly on low-probability, high-consequence outages (Hanna and Marqusee 2022).

We developed a methodology that estimates customer outage duration from customer outage time-series data from the EAGLE-I data set collected by researchers at DOE's Oak Ridge National Laboratory (ORNL). We combined these results with information on the average frequency and duration of major outage events to estimate outage recurrence intervals and conditional exceedance probabilities. Because hurricanes and PSPS events are two leading causes of extended-duration power outages, we calculated outage duration frequencies for these specific event types as well. Recurrence intervals are commonly used in the analysis of low-frequency, high-impact events, such as flood risks being described in terms of 100-year floods, and they are the reciprocal of the annual probability of occurrence. The consequence of an outage event can be divided by its recurrence interval to determine its expected annual risk, meaning recurrence intervals are an important input for probabilistic risk assessments of the benefits of resilience investments. Exceedance probabilities are useful for translating hazards into outage impacts and can inform outage durations chosen in scenario analyses.

The outage duration estimates presented in this report can support resilience investment decision making and can be integrated into resilience analysis tools. Tools such as FEMA's Benefit-Cost

Analysis (BCA) Toolkit (FEMA 2019) or the Pacific Northwest National Laboratory's (PNNL's) Technical Resilience Navigator (PNNL 2022) require outage frequency inputs, and users of such tools can benefit from the results presented in this report. Current sources of outage frequency information include utility reported average interruption durations (EIA 2021), reported loss of off-site power at nuclear power plants (Johnson and Ma 2021), reports from major outage events (DOE 2022), or individual outage case studies. Although these data sources are valuable, they can suffer from not providing outage duration distributions, a lack of granularity, data quality issues, and small sample sizes.

Outage duration estimates developed using our methodology have been integrated into the National Renewable Energy Laboratory's (NREL) Customer Damage Function (CDF) Calculator (NREL 2022). The CDF Calculator is a resource for facility managers to understand the costs incurred at their site from an electric grid outage. A CDF relates outage durations to interruption costs, accounting for nonlinearities in costs with respect to duration. By combining the CDF with outage duration estimates, it is possible to estimate expected annual outage costs, which can inform the cost of inaction and the value of resilience from the investment. Beyond providing values that are useful to resilience tools, the results presented in this report help to fill a broader gap in our understanding of extended power outages.

This paper summarizes the role power outage data play in resilience assessments. Section 2 summarizes the data sets used. Section 3 provides an overview of power outages, details the major causes of extended power outages, and provides customer and outage summary statistics by region. Section 4 details the methodology used to convert customer outage information into outage duration estimates. Section 5 applies the methodology to California's PSPS events, discusses how the methodology was calibrated to the PSPS event data, and provides estimates for PSPS events. Section 6 presents outage duration probabilities for major hurricanes. Finally, Section 7 presents duration probabilities and recurrence intervals for major outage events by region.

2 Data

Our primary source of outage information is from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I™) data set, provided by ORNL.[5] The EAGLE-I data were supplemented with state-level outage information provided by the U.S. Energy Information Administration (EIA) Form 861 (EIA 2021). We also incorporate information on major power outage events from the OE-417 data set (DOE 2022, 4). We include information on hurricane-caused power outages from DOE's emergency situation reports and data related to California's PSPS outages provided at the circuit level by the California Public Utilities Commission (CPUC). Table 1 summarizes the data sets used.

Table 1. Summary of Data Sets Used in Analysis Along With Time Frame Used/ Available at Time of Analysis

Data Set	Source	Time Frame	Description
EAGLE-I[a]	ORNL	Nov. 2014–March 2021	Customer outages at 15-minute intervals by utility within each county
Form EIA-861[b]	EIA	Jan. 2013–Dec. 2020	Utility information, including SAIFI and SAIDI, with and without MEDs, by utility and state
OE-417[c]	DOE	Jan. 2015–Dec. 2021	Information on major power outage events, including outage times, areas affected, and peak customer outages
Emergency situation reports[d]	DOE	Jan. 2003–Dec. 2021	Descriptions of customer outages by state and time for major hurricanes and other impactful events
PSPS post-event reports[e]	CPUC	Oct. 2013–Dec. 2021	Circuit-level information on time and duration of California's PSPS.

[a] EAGLE-I: https://EAGLE-I.doe.gov/login
[b] Form EIA-861: https://www.eia.gov/electricity/data/eia861/
[c] OE-417: https://www.oe.netl.doe.gov/OE417_annual_summary.aspx
[d] Emergency situation reports: https://www.energy.gov/ceser/activities/energy-security/monitoring-reporting-analysis/emergency-situation-reports
[e] PSPS post-event reports: https://www.cpuc.ca.gov/consumer-support/psps/utility-company-psps-reports-post-event-and-post-season.

2.1 EAGLE-I

The EAGLE-I data contain information on the number of customers without power at 15-minute intervals by utility within each county.[6] The EAGLE-I data are compiled by ORNL from scraping utility websites that report current customer outage rates and durations. The data span from November 2014 to March 2021 and provide a highly granular spatiotemporal view of power outages across the United States. Table 2 displays a sample of EAGLE-I data for July 1, 2015, in three Gulf Coast states. Each observation is for utility customer outages for a given county and a given 15-minute time interval, where counties are identified both by state and

[5] The EAGLE-I tool can be accessed at https://EAGLE-I.doe.gov/login.
[6] Many counties have only a single utility, but for counties that have multiple utilities, customer outages are provided for each utility.

county name and by the Federal Information Processing Standards (FIPS) code, which is a unique number for each county.

Table 2. Sample EAGLE-I Data

utility_id	utility_name	fips_code	County	State	outage_count	run_start_time
131	Entergy Louisiana	22019	Calcasieu	Louisiana	3	7/1/2015 10:30
131	Entergy Louisiana	22051	Jefferson	Louisiana	155	7/1/2015 10:30
132	Entergy Mississippi	28113	Pike	Mississippi	60	7/1/2015 10:30
132	Entergy Mississippi	28033	DeSoto	Mississippi	47	7/1/2015 10:30
132	Entergy Mississippi	28049	Hinds	Mississippi	15	7/1/2015 10:30
133	Entergy Texas	48361	Orange	Texas	18	7/1/2015 10:30

Because of the unique characteristics of power outages on islands and in Alaska, we restrict our analysis to counties in the contiguous United States. The data do not cover all counties, and the number of counties included changes with time. Table 3 shows the number of counties tracked by EAGLE-I by year of the 3,108 total counties in the contiguous United States. Because EAGLE-I provides an incomplete and unbalanced[7] panel data set, additional steps would be required before it could be used to estimate total outages or year-over-year changes in outages.[8] In raw form, the EAGLE-I data also cannot be used to estimate the distribution of customer power outage durations; however, the process described in Section 4 allows data to be converted to a form that provides insights into customer power outage durations.

Table 3. Counties in Contiguous United States Tracked in EAGLE-I Data by Year

Year	2015	2016	2017	2018	2019	2020	Total Counties
Counties	2,153	2,499	2,548	2,880	2,893	3,014	3,108

2.2 OE-417 Major Outage Events

DOE's Office of Electric Delivery and Energy Reliability collects electric disturbance reports, called OE-417 (DOE 2020), which are mandatory reports for balancing authorities, reliability coordinators, some generating entities, and electric utilities that experience a disruptive event. OE-417 reports are filed when one or more of 26 criteria are met. Several criteria, such as cyber threats or vandalism, might not result in customer outages; however, because filings are required when 300 MW of firm load are shed (200 for smaller entities) for 15 minutes or more, or when

[7] When describing panel data, *incomplete* refers to the case when not all panel members are included in the data set, and *unbalanced* refers to the case when some panel members are included only for a subset of the years.

[8] Because of the high-level coverage the EAGLE-I data now have, they might be able to be used for such analyses going forward.

50,000 or more customers are without power for more than 1 hour, OE-417 reports contain information on when and where widespread outages occurred. We subset the OE-417 data to events resulting in power outages that impact at least 10,000 customers to generate a list of 620 unique major outage events between January 1, 2015, and December 31, 2021.

The OE-417 data are of insufficient quality to estimate outage durations for two reasons: Customer outages are not always tracked and are sometimes incorrect, and reported outage durations often far exceed what the average customer experiences.[9] OE-417 data do, however, provide valuable information on start dates, end dates, and locations for major outage events. Outage event times and locations from the 620 outages identified from the OE-417 data were linked to EAGLE-I outage information through outage event time and states impacted to create a panel data set of customer outages by county during major outage events.

2.3 Form EIA-861

Electric power utilities use three main calculations to indicate system performance: System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Customer Average Interruption Duration Index (CAIDI). CAIDI, which can be calculated by dividing SAIDI by SAIFI, provides the average outage duration a customer would experience.

System performance indices can be calculated with or without including major event days (MEDs). Excluding MEDs allows utility regulators to focus on the day-to-day reliability of the system. At the same time, major events constitute a significant share of the total outage minutes customers experience. MEDs are calculated differently for different utilities, but generally they are determined based on days when the number of customer outage minutes exceeds a given threshold. We obtained SAIDI and SAIFI values for MED outages by subtracting SAIDI and SAIFI values for nonmajor events from total SAIDI and SAIFI values, which then allows for the calculation of CAIDI for MED outages.

The *Annual Electric Power Industry Report, Form EIA-861* (EIA 2021) contains detailed information regarding U.S. utilities. Form EIA-861 provides information on SAIDI, SAIFI, and CAIDI with and without MEDs by utility and state from 2013–2020.[10] Form EIA-861 also provides utility information, such as number of customers and electricity usage.

Although they are sufficient for modeling shorter-duration power outages, SAIFI, SAIDI, and CAIDI do not provide sufficient information to determine the distribution of extended outage durations; thus, these values alone are insufficient for resilience planning. At the same time, the EAGLE-I data do not cover all counties and do not contain information on total customers and

[9] A general challenge of using data aggregated to outage events to estimate outage durations is that outage durations are often measured from when the first customer outage is reported to when the last customer is restored. The average outage duration is almost always shorter than this duration, and unless the first customer whose power went out is the last to be restored, then all customers experience a shorter outage duration that the duration in the data.
[10] SAIFI measures the average number of outages exceeding 5 minutes that customers experience, and SAIDI measures the average number of outage minutes customers experience. MEDs are classified when the daily SAIDI exceeds a threshold, where the threshold is determined by the Beta method (Warren et al. 2001).

are therefore insufficient to calculate average outage durations. We produced duration curves from the analysis of the EAGLE-I data to determine the distribution of major outage durations. This distribution was then combined with EIA-provided average outage statistics to determine expected outage probabilities and recurrence intervals.

2.4 Public Safety Power Shutoff Events

California utilities will de-energize power lines during periods of high wildfire risk to reduce the chance of fires. The CPUC requires utilities to report PSPS events and provides data at the circuit level related to time, duration, and number of customers impacted. Table 4 displays a sample subset of the data. The data span from October 2013 through December 2021, though almost all PSPS events occurred in or after 2017.

Table 4. Sample PSPS Event Data[a]

Utility	Outage Start (Date and Time)	Full Restoration (Date and Time)	Total Outage Hours	Circuit Name	Number of Customers Impacted
PacifiCorp	8/17/2021 15:48	8/17/2021 20:34	4.77	8G65	170
PacifiCorp	8/17/2021 16:12	8/17/2021 22:02	5.83	8G95	290
PG&E	10/26/2019 20:19	10/28/2019 20:44	48.42	ALHAMBRA-1105	1712
PG&E	10/14/2020 10:30	10/16/2020 11:07	48.62	ALLEGHANY 1101	957
PG&E	9/7/2020 21:57	9/10/2020 16:31	66.57	ALLEGHANY 1101	1028

[a] Some columns of the acutal data are omitted.

The PSPS event data do not have counties associated with the circuits, so a crosswalk was conducted between circuits and counties to correlate with the EAGLE-I data. Because the outage duration time is from when the first customer was de-energized until full restoration, the outage duration for the mean or median customer will often be shorter than reported. The PSPS event data are valuable both for estimating durations and for calibrating the methodology that transforms the EAGLE-I data into customer outage durations.

2.5 Major Hurricane Events

DOE produces emergency situation reports to capture details of events that cause extensive power outages.[11] The data contained in these reports were used to determine the timing of and the states impacted by seven major hurricanes that caused extended outages to the contiguous United States and occurred during the sample period covered by EAGLE-I data. These hurricanes are detailed in Table 5. Note that Hurricane Maria had a limited impact on the contiguous United States during this period, so it was omitted, though it caused widespread

[11] Emergency situation reports can be accessed at https://www.energy.gov/ceser/activities/energy-security/monitoring-reporting-analysis/emergency-situation-reports.

devastation to the Puerto Rico power grid, resulting in the longest-duration outage (i.e., 11 months) in U.S. history.

Table 5. Subset of Major Hurricanes During Sample Period[a]

Hurricane	States	Start Date	End Date
Harvey	TX	8/26/2017	9/7/2017
Irma	FL, GA, SC, NC	9/13/2017	9/25/2017
Florence	SC, NC	9/18/2018	9/23/2018
Michael	FL, AL, GA, NC, SC	10/10/2018	10/19/2018
Matthew	FL, GA, SC, NC, VA	10/8/2016	10/14/2016
Barry	LA, FL, GA, SC, NC, VA, LA	7/12/2019	7/15/2019
Ida	LA	8/28/2021	9/23/2021

[a] Values were determined from DOE's emergency situation reports.

3 Overview of Power Outages

Access to electricity is central to modern life. The electric grid comprises a system of generators and storage assets (both centralized and distributed) connected to end customers through a network of transmission and distribution infrastructure. Power outages can be caused by insufficient generation or capacity to meet demand, though most are caused by disruption to components along transmission lines and to the distribution grid.

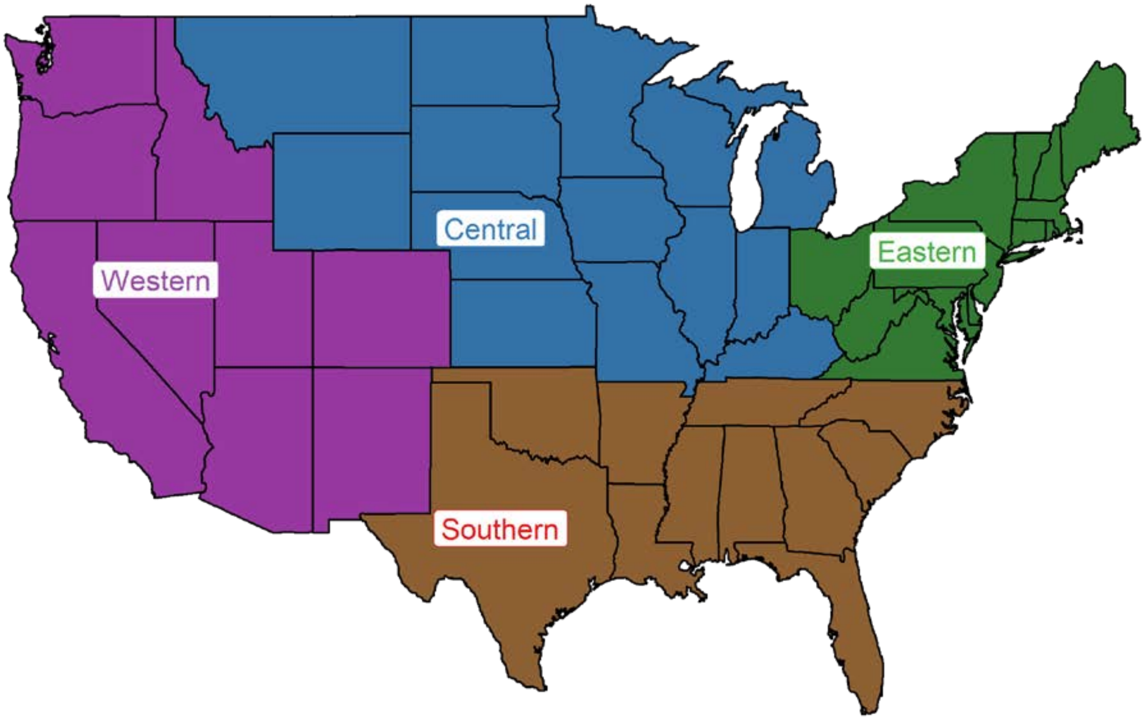
Most power outage events are minor disturbances to the distribution grid (Silverstein et al. 2018). These disturbances are generally a result of events such as animals (e.g., squirrels) or vegetation (e.g., downed trees or branches) shorting the line, inclement weather (e.g., lightning or high winds), equipment failure such as a transformer breaking, or human error such as a driver striking a utility pole (Eaton 2018). Minor disturbances affect a small number of customers, and power tends to be restored relatively quickly.

Although most outage events are minor disturbances, most outage minutes customers experience are caused by major events impacting a wide area and lasting up to several days. Such major events are primarily caused by winter storms and hurricanes but are also increasingly being caused by wildfires and the threat of wildfires leading to PSPS. Hurricane outages and PSPS events were closely examined in this report because of their importance in extended outage durations and the relative ease of linking these hazards to outages. We leave the valuable work of estimating exceedance probabilities for other hazards to future research.

Outages caused by wildfires and hurricanes are expected to increase in the coming years as a consequence of climate change (Finster et al. 2016) and aging infrastructure, and physical and cyberattacks are also expected to increase (Reidmiller et al. 2018; Sanstad et al. 2020). Work to forecast future hazard frequencies would be valuable for determining the risk of future power outages.

3.1 U.S. Regions

Outage probabilities vary by location because the underlying hazards that cause outages vary by location. Finer geographic detail more accurately captures the underlying hazards of a specific region and can produce more accurate estimates. At the same time, modeling more regions reduces the number of observations for each location. Because high-impact events occur with low frequency, maintaining large sample sizes within regions is important for limiting statistical error. The appendix provides results for the nine National Centers for Environmental Information climactically consistent climate regions (Karl and Koss 1984). As shown in Figure 1, we further combine these regions into four regions. This is only one of many potential ways to aggregate U.S. counties into regions. Future work could examine the connection between counties and specific hazards that cause grid outages to more effectively aggregate regions with regard to power outages.



Region	States	Land Area (Mi^2)	Population (Million)
Central	IL, IN, IA, KS, KY, MI, MN, MO, MT, NE, ND, OH, SD, WI	913,000	63
Eastern	CT, DE, DC, MA, ME, MD, NH, NJ, NY, PA, RI, VT, VA, WV	279,000	87
Southern	AL, AR, FL, GA, LA, MS, NC, OK, SC, TN, TX	756,000	104
Western	AZ, CA, CO, ID, NM, NV, OR, UT, WA	932,000	75

Figure 1. U.S. regions used for analysis

3.2 Outage Average Statistics by Year and Region

Table 6 displays annual SAIFI and CAIDI by region including MEDs, calculated from Form EIA-861 data. Table 7 displays the same values for only MED events. On average, customers experience a major outage event that lasts an average of 11 hours once every 3–4 years. The southern region has the highest prevalence of major outages because of the impact of hurricanes, which are the leading cause of major power outages (Alemazkoor et al. 2020).

Table 6. SAIFI and CAIDI Averages by Region Including MEDs[a]

Year	SAIFI with MEDs (Events per Year)				CAIDI with MEDs (Min)			
	Central	**Eastern**	**Southern**	**Western**	**Central**	**Eastern**	**Southern**	**Western**
Average	1.173	1.236	1.609	1.057	220	241	267	189
2013	1.243	1.176	1.397	0.902	260	212	131	129
2014	1.162	1.181	1.440	1.003	209	197	170	142
2015	1.201	1.051	1.568	1.040	175	163	154	178
2016	1.134	1.161	1.657	1.060	173	149	256	134
2017	1.147	1.176	1.848	1.229	250	247	500	176
2018	1.144	1.445	1.542	0.996	195	329	280	176
2019	1.236	1.295	1.513	1.151	209	205	166	335
2020	1.120	1.405	1.906	1.078	291	378	384	222

[a] Values were derived from Form EIA-861.

Table 7. SAIFI and CAIDI Averages by Region for Only MEDs[a]

Year	**SAIFI MED Only (Events per Year)**				**CAIDI MED only (Min)**			
	Central	Eastern	Southern	Western	Central	Eastern	Southern	Western
Average	0.228	0.257	0.387	0.196	633	702	779	520
2013	0.296	0.226	0.228	0.079	703	598	321	338
2014	0.188	0.223	0.248	0.129	679	548	515	337
2015	0.181	0.090	0.302	0.194	534	663	372	453
2016	0.190	0.133	0.383	0.164	418	390	761	270
2017	0.261	0.245	0.624	0.343	677	723	1273	333
2018	0.210	0.414	0.349	0.152	518	842	868	523
2019	0.255	0.312	0.344	0.292	533	457	351	974
2020	0.245	0.418	0.620	0.219	908	979	954	625

[a] Values were derived from Form EIA-861.

3.3 Weather Events

Weather-related hazards tend to have an associated season where events are most common. Each hazard also has an associated distribution of outage durations. Table 8 displays the number of storm events tracked by the National Oceanic and Atmospheric Administration (NOAA) that occurred between 1996 and 2021 (NOAA 2022). Hurricanes and tropical storms affect the eastern and southern regions, wildfires are most prominent in the western regions, and winter storm events occur most frequently in the central region.

Table 8. Storm Events by Region 1996–2021[a]

Region	Flood	Heat	Hurricane/ Tropical Storm	Tornado	Wildfire	Wind	Winter Event
Central	15,284	1,104	1	3,962	527	35,601	53,348
Eastern	13,640	1,139	99	852	235	23,708	17,971
Southern	14,175	1,360	673	4,843	1,751	42,807	33,533
Western	7,168	788	3	908	3,168	11,999	16,905

Data are compiled from NOAA's Storm Events Database (NOAA 2022).

Figure 2 displays the distribution of select hazards across the United States. Colored areas denote the 10% of counties wich experience the highest frequency of events. Hazard frequency information comes from FEMA's National Risk Index database (Zuzak et al. 2022). The geographic component of risk is apparent, with the threat of underlying hazards varying significantly by state and region. Even within regions, the frequency of hazards varies. Power outage frequencies depend on the frequency, type, and intensity of underlying hazards along with the vulnerability of the grid to these hazards. Future research could improve outage estimates by linking underlying hazard frequencies with outage frequencies by duration.

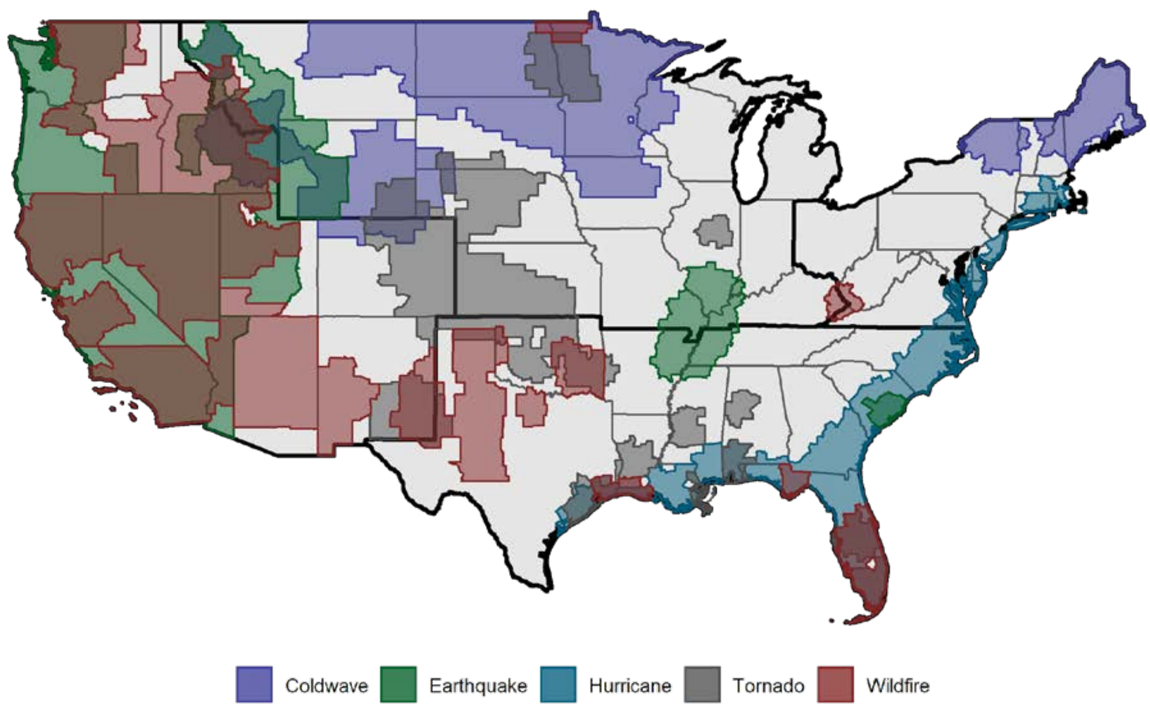


Figure 2. Map of select hazards. Colors denote counties in the top 10% highest occurrence frequency for a given hazard.

Data are from FEMA's National Risk Index Database, https://hazards.fema.gov/nri/. Source: Zuzak et al. (2022)

4 Methodology

Customer-level outage duration information by outage event is not available to researchers, but granular customer outage data by time and county do exist through the EAGLE-I data set. Therefore, we developed an algorithm to transform customer outage time-series data into customer outage duration estimates.

Figure 3 displays customer outages for Jefferson County, Texas, during Hurricane Harvey in 2017. The Jefferson County outages display the shape common to most large-scale outage events, with some outages occurring before the event, then total customer outages ramping up to a peak and then declining, albeit nonmonotonically, until power is restored to all customers.

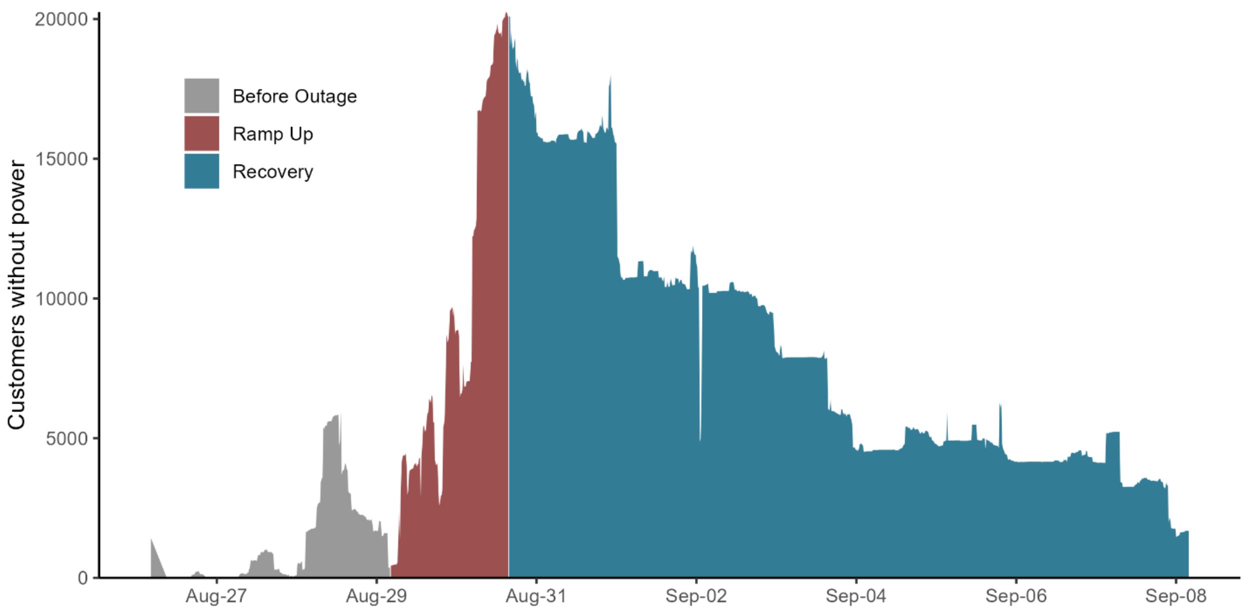


Figure 3. Customer outages for Jefferson County, Texas, during Hurricane Harvey

Data are from the EAGLE-I data set.

Step one in estimating customer outage duration is to address data quality issues, such as the large momentary dip on September 2, which is not representative of a true change in customer outages. The EAGLE-I data come from scraping utility websites, and occasionally these websites might go down or report incorrect values. We aggregate outages to 4-hour intervals and set customer outages to the maximum number of customer outages reported in each interval. The 4-hour interval removes most data quality issues, and using the maximum number of customer outages during the interval is preferred to using averages because the average would still be impacted by periods where outage counts are artificially low. [12]

Step two identifies outage events. We do this by using additional information, such as OE-417 outage event reports, DOE emergency situation reports for hurricanes, or CPUC information on PSPS events. We focus on major outage events both because they are the primary cause of

[12] EAGLE-I attempts to avoid overreporting outages by reporting zero outages when utility websites go down.

extended outages and because we can use these additional resources to identify them when they occur.

Step three determines when an outage event begins. Although in many cases it is clear when an outage event occurs, in other cases, it might not be as straightforward. In Figure 3, for example, the initial increase, and then decrease, in customer outages on August 28 might be separate outage event or could be part of the same outage. We use the heuristic that an outage event begins in the first period where customer outages exceed 25% of peak outages.[13]

Step four determines the algorithm's peak period as the first time period when customer outages exceed 75% of the actual peak customer outages. This period coincides with the actual peak for many outages and provides a balance for cases where the peak occurs well after most customers are already without power.

Step five calculates a monotonically decreasing sequence[14] of customer outages from the algorithmic peak to determine the algorithm's customer outages in each period. That is, the algorithm's customer outages for a period are the lesser of the reported customer outages for that period and the algorithm's customer outages for the previous period (i.e., we remove any secondary peaks from the outage data). Taking a monotonically decreasing sequence alleviates the problem of when the total customer outages decrease and then later increase, which is a problem because without individual customer information, it is unclear how long each customer experiences an outage.

Step six calculates a shifting factor to account for the ramp-up period of an outage. Most customers are without power before the peak outage period, but most customers are not without power from the start of the outage event. Thus, we multiply the time between the outage start and the peak outage period by a shifting factor ratio, r. As discussed in Section 5, we calibrate r to be 0.75. For example, if the peak outage period occurs 24 hours after the outage start period, then the shifting factor would be 18 hours (24 times 0.75). To account for cases where the outage start was incorrectly identified and to avoid overestimating outage durations, we limit the maximum shifting factor, f_{max}, to be 24 hours.

Step seven, the final step in our process, returns customer outage duration estimates. In each period after the peak outage period, we calculate the outage duration, d, as the shifting factor plus the time from the peak outage period. The number of customers to experience an outage of a duration, d, is estimated by the difference between the algorithm's customer outages in that period and the previous period. If 1,000 customers are without power at the peak and 600 customers are without power 1 day after the peak, then 400 customers experienced less than a 1-day outage.

We assume that the composition of customers experiencing an outage does not change throughout the outage event. If 100 customers are reported without power for 1 day, we assume they are the same 100 customers without power for each of the 24 hours. This assumption could

[13] Our heuristic would mark the outage starting around the August 28th peak given customer outages exceed 25% of the peak customer outages.
[14] A *monotonically decreasing sequence* is when the sequence gets progressively smaller.

overestimate outage durations in the case of rolling blackouts or events that impact different regions at different times, where the same total number of customers could be without power but the composition of which customers are without power varies.

The steps of the algorithm to estimate customer outage durations are summarized as follows:

1. **Aggregate data.** Set *C(t),* which denotes the customer outages in an interval, *t,* to the maximum number of customer outages in the 4-hour period, from t to t + 4. Let C_P denote the peak number of customer outages.
2. **Identify the outage periods.** Run the algorithm for each county for each expected outage period plus a buffer period.
3. **Determine the start period.** The start period, T_S, is the first period where C(t) > 0.25 C_P.
4. **Determine the peak period.** The peak period, T_P, is the first period where C(t) > 0.75 C_P.
5. **Calculate the algorithm's customer outages, A(t):**

$$A(t) = 0 \; for \; all \; t < T_P$$
$$A(T_P) = C(T_P)$$
$$A(t) = \min\big(A(t-1), C(t)\big) \; for \; all \; t > T_P$$

   These steps produce a monotonically decreasing series of customer outages beginning at the peak period.

6. **Calculate the duration shifting factor.** The duration shifting factor, *f*, is given by:

$$f = \min((T_P - T_S) \times r, f_{max})$$

   where r is the calibrated shifting factor ratio of ¾, and f_{max} is the maximum shifting factor set to 24 hours.

7. **Calculate the customer outages by duration.** For each interval after T_P, the outage duration is given by $d(t) = t - T_P + f$, and X*(d),* the number of customers who experience an outage of duration, d, is given by $X(d) = A(t) - A(t+1)$.

Figure 4 shows the algorithmically derived customer outages, A(t), for six Texas counties during Hurricane Harvey. The gray line denotes the number of customer outages reported by the EAGLE-I data. These values are then transformed into customer outage durations by using steps 6 and 7.

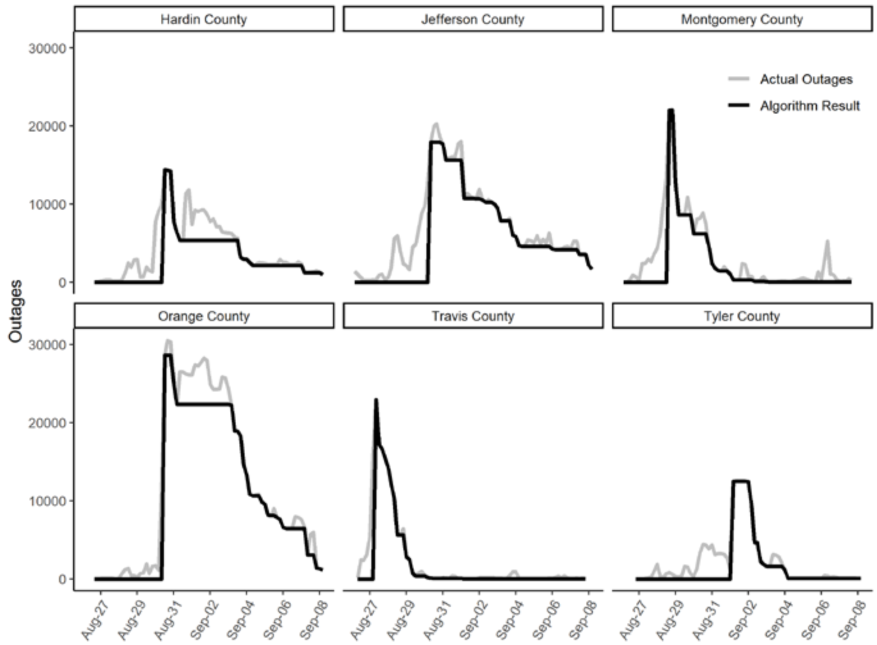


Figure 4. Algorithm results for Hurricane Harvey for the six Texas counties with the highest number of peak outages

Figure 5 displays the exceedance probabilities for the six Texas counties during Hurricane Harvey. The exceedance probability curves are calculated by taking the number of customers remaining without power and dividing by the peak number of customer outages. The duration for the exceedance curve is given by d(t), as calculated in Step 7.

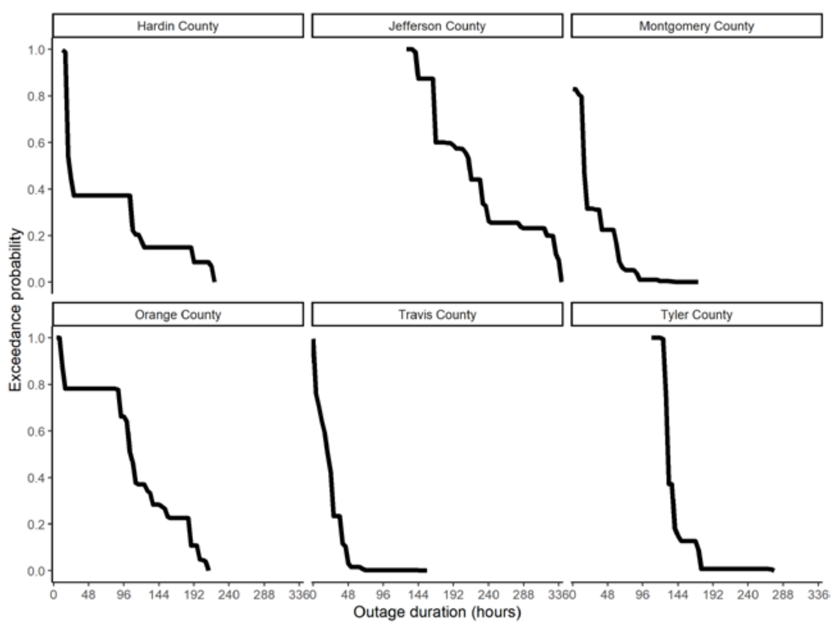


Figure 5. Exceedance probabilities for Hurricane Harvey for the six counties with the highest number of peak outages

5 California Public Safety Power Shutoff Events

In the West, particularly in California, utilities are de-energizing transmission lines to reduce the chance of wildfires. These PSPS events result in widespread extended outages, with customers sometimes losing power for multiple days. Utilities are required to report PSPS event outage durations to the utility commission, which are then made publicly available. Figure 6 shows the distribution of customer outage durations reported by the CPUC. These data allow us to calibrate and test the methodology for estimating outage durations, which can then be applied to a broader range of outage types.

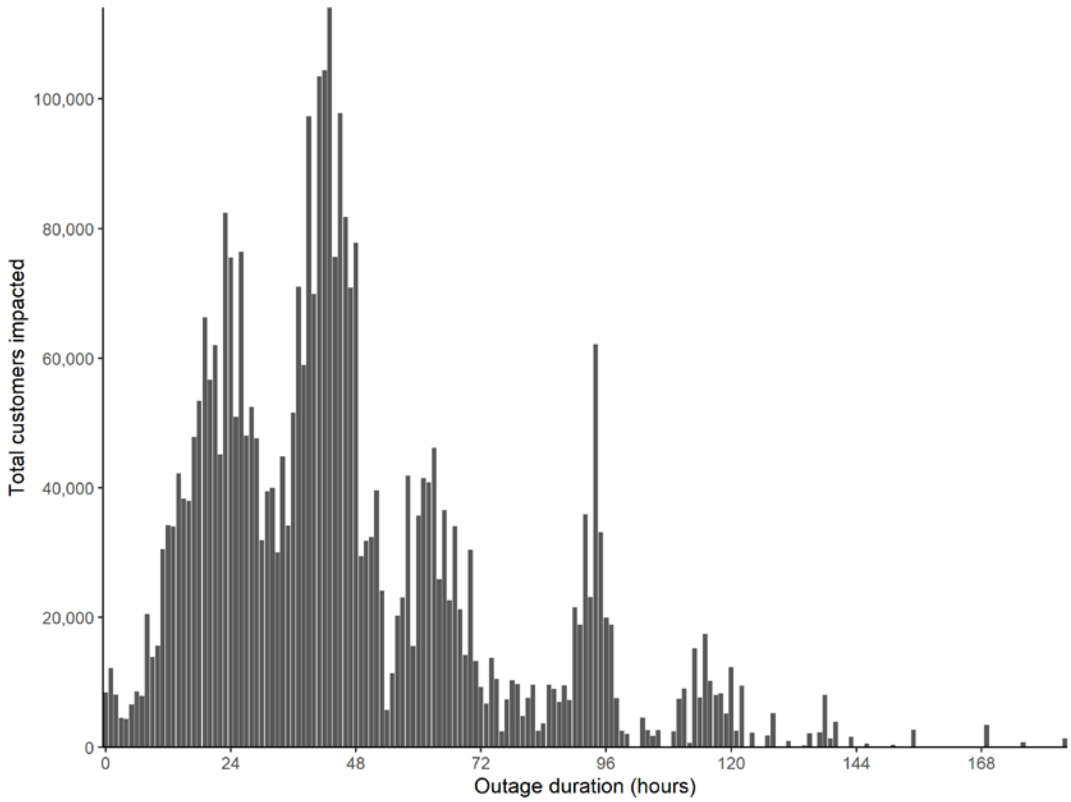


Figure 6. Outage durations for California PSPS events

Data at the circuit level were provided by the CPUC.

To compare across data sets, circuit-level outage data provided by the CPUC were aggregated to the county level.[15] Figure 7 displays customer outages reported by the CPUC and EAGLE-I data for October 9–13, 2019, during a PSPS event in the Pacific Gas & Electric Company (PG&E) territory. The two data sets match remarkably well, which gives confidence to the use of the EAGLE-I data for calculating outage statistics. Note that the EAGLE-I customer outages tend to decrease more quickly than the CPUC data, something that is particularly pronounced in Solano County, as shown in Figure 7. This is partially caused by the CPUC outage durations being calculated as the time from the first outage to the last recovery by feeder. Thus, the average

[15] A note to future researchers: The EAGLE-I data outage times are in Eastern Standard Time, which requires each time stamp to be subtracted by 3 hours to match the California outages.

customer at many feeders has their power restored before the outage event ends, which results in the CPUC data overestimating outage durations for many customers.

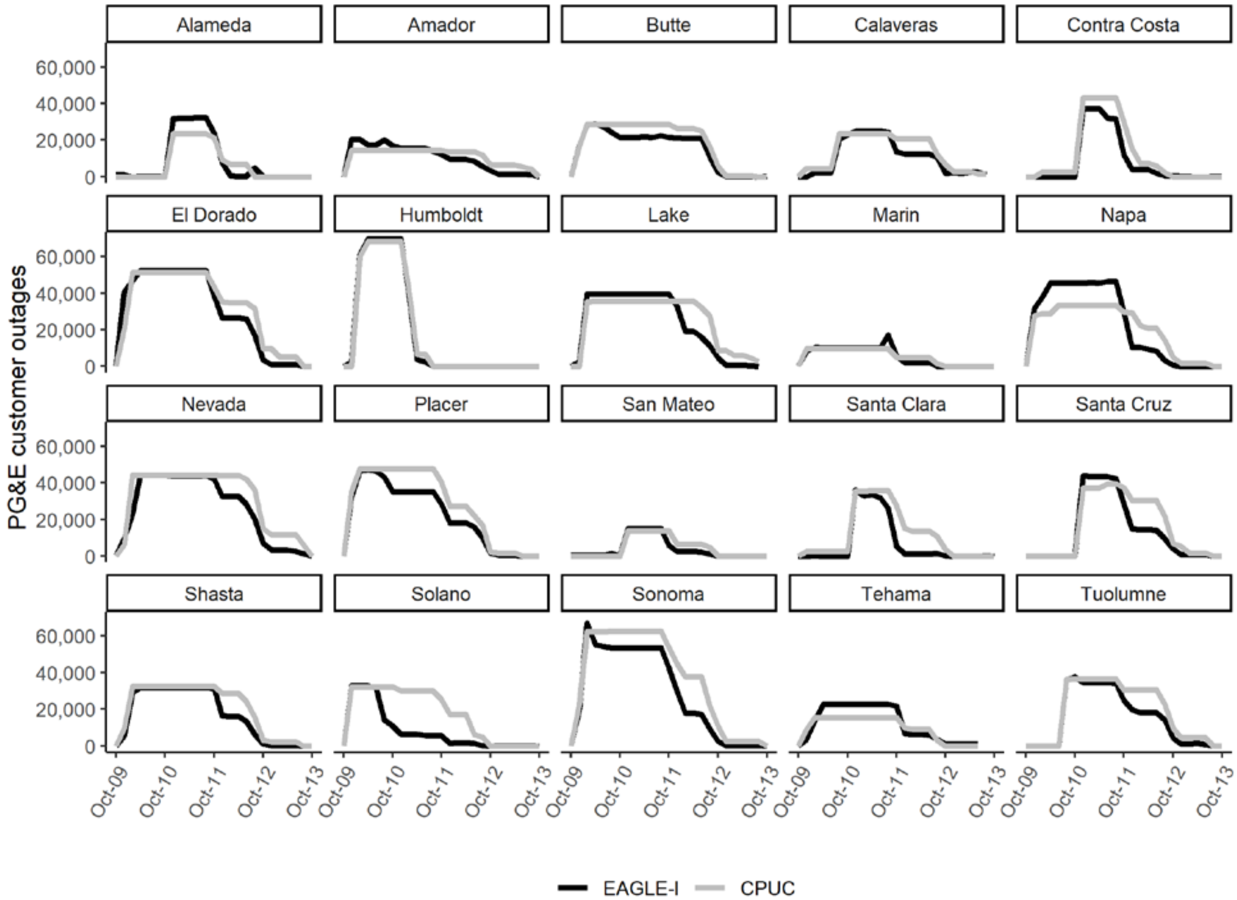


Figure 7. Customer outage information by county for October 2019 PG&E PSPS event for counties with at least 9,000 outages

Figure 8 displays the exceedance probability curves estimated from the algorithm described in Section 4 applied to the EAGLE-I data for the same counties and event along with the exceedance probability curves calculated from the CPUC circuit-level outage data. For many counties, the two curves match closely, and in almost all counties, the curves match well toward the end of the outage duration. For counties where the curves do not coincide closely, the differences might be attributed to data quality issues with the EAGLE-I data,[16] data quality issues with the CPUC data,[17] issues with the crosswalk to counties,[18] or denote a failing of the algorithm. Additional work could further improve the approach of converting customer outages

[16] EAGLE-I depends on the utility reporting of outage information, which can become inaccurate during major outage events; however, this does not seem to be a concern during any of the PSPS events.
[17] Load-serving entities in California are required to report PSPS outages, so the reported information is of high quality; however, customer outage durations are reported from the first outage to the final recovery, which can overstate the number of customers without power.
[18] Because only a small number of circuits were not successfully matched, this likely does not have a meaningful impact.

to outage duration estimates, such as by increasing the robustness of determining outage starts, better determining customer outages for shorter-duration events, and accounting for cases where customer outages nonmonotonically decline. At the same time, the accuracy of our approach for many of the counties gives us confidence that our approach can produce meaningfully accurate estimates.

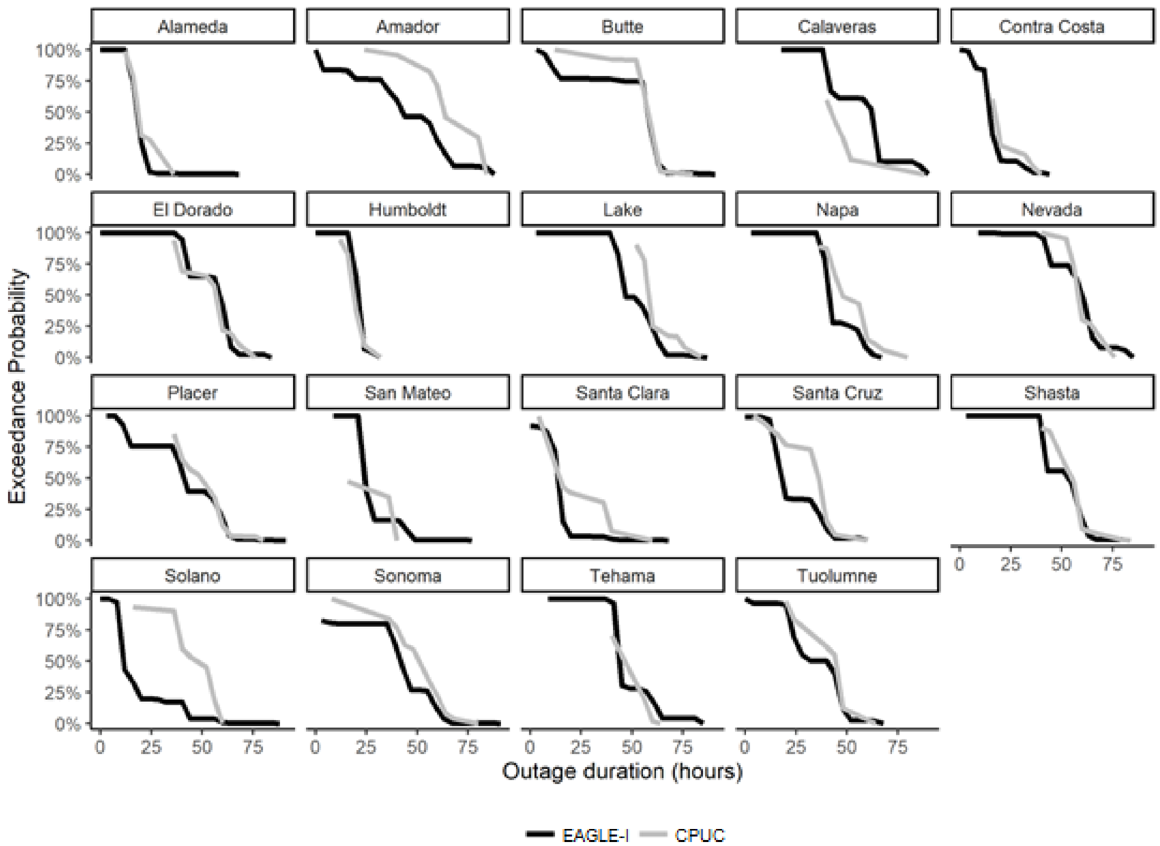


Figure 8. Exceedance probability curves estimated from the algorithm and computed from CPUC information. Customer outage information by county for October 2019 PG&E PSPS event for counties with at least 10,000 outages

Figure 9 displays the exceedance probability curve calculated from the CPUC circuit-level data along with the exceedance probability curve from applying the methodology described in Section 4 to the counties and times with PSPS outage events. The dotted line shows the exceedance probability curve if the shift factor is not applied. Comparing the dotted line to the gray line, the methodology captures the underlying data, but starting the outage durations at the peak outage period underestimates the outage durations. Once the shift factor is applied, the estimated exceedance probability curve aligns well with the exceedance probability curve derived from the CPUC data.

The shift factor captures the fact that customer outages begin before the algorithm's peak, but most customers do not lose power at the start of the outage period. Instead, most customers experience an outage that starts somewhere between the outage start period and the outage peak period. We use the shift factor of ¾ because the root mean square error between the exceedance probability calculated from the CPUC circuit data and the methodology applied to the EAGLE-I data is minimized between 23/32 and 24/32. The close fit between the two curves provides a measure of confidence that the methodology can convert customer outage information into meaningfully accurate outage duration estimates.

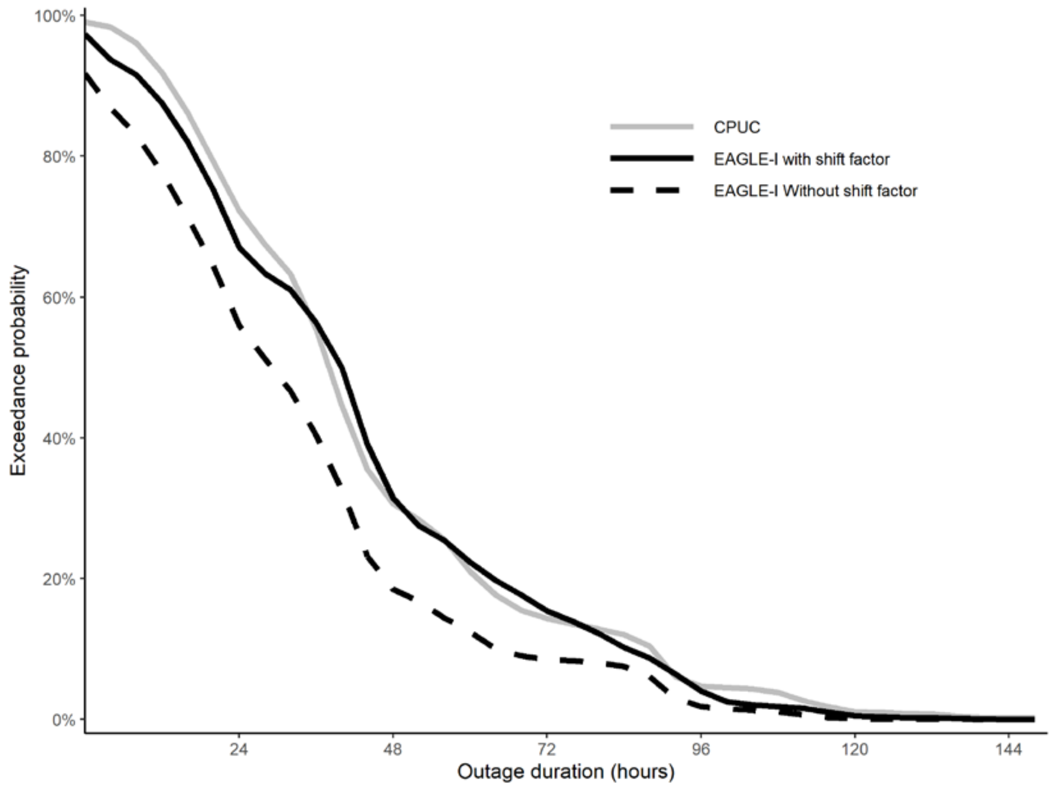


Figure 9. Exceedance probability curves for PSPS outage durations, calculated from CPUC circuit-level data and EAGLE-I county-level data

Table 9 displays the exceedance probabilities calculated by applying the methodology to the EAGLE-I data after sub-setting to county-time intervals where PSPS events occurred. Table 9 also displays the exceedance probabilities calculated from the CPUC circuit-level outage data. The estimated exceedance values closely track the CPUC results, though the EAGLE-I data tends to provide conservative duration estimates. In particular, the methodology overcounts short-duration outages and undercounts long-duration outages relative to the CPUC results.

The underestimation of long-duration outages compared to the results using the CPUC duration data is partly because the CPUC reported values overestimate long-duration outages because they report durations as occurring from the first outage to the last recovered. It is very likely partly caused by limitations in the accuracy of our methodology as well. Probability estimates of very long outages are especially challenging because of the rare nature of such outage events. A 0.1% or even a 0.01% difference in the estimated chance of occurrence can result in drastic differences in outage recurrence rates. As a concrete example, of the nearly 3.6 million PSPS customer outages reported by the CPUC, only 5,472, or 0.1%, lasted 1 week or longer. Probability distributions for power outages are also marked by fat tails for long-duration outages, meaning low-probability, but high-consequence events comprise a meaningful fraction of total outage minutes the customers experience. Thus, caution is a must when using estimates for the likelihood of outage durations exceeding 5 days or 1 week. At the same time, we believe our results provide a good starting point for resilience decision making, and additional work on the methodology or additional data on outages could further refine the accuracy of our results.

Table 9. Outage Exceedance Probabilities for California PSPS Events[a]

Outage Duration Hours (Days)	EAGLE-I Estimated Exceedance Probabilities	CPUC Calculated Exceedance Probabilities
12 (.5)	87.3%	91.9%
24 (1)	66.3%	72.3%
48 (2)	29.8%	30.7%
72 (3)	13.1%	14.3%
96 (4)	3.3%	4.7%
120 (5)	0.4%	1.1%
144 (6)	0.012%	0.24%

[a] Values were estimated by applying the methodology to EAGLE-I data and by calculating the results from CPUC circuit-level outage data.

Table 10 presents the probability that a PSPS outage duration will fall within a given duration interval. These two tables show that, given a de-energization event occurs, it is likely that the outage will last at least 1 day. Thus, backup systems in areas prone to wildfires and PSPS events should be designed to survive multiday outages. It is also unlikely that the outage duration will exceed 1 week. Therefore, preparing a backup system to survive a month-long outage in anticipation of a PSPS might be excessive, with the costs of such upgrades perhaps being better spent on other needs.

Table 10. Probabilities for PSPS Outage Duration Falls Within a Given Interval[a]

Duration Interval	Eagle-I Estimates	CPUC Reported Results
0– 2 hours	12.7%	8.1%
12–24 hours	21.0%	19.6%
1–2 days	36.4%	41.6%
2–3 days	16.7%	16.3%
3–5 days	12.7%	13.2%
5–7 days	0.4%	1.0%

[a] Values were estimated by applying the methodology to EAGLE-I data and by calculating the results from the CPUC circuit-level outage data.

6 Major Hurricane Outages

Hurricanes are some of the most damaging weather events and are primary causes of long-duration power outages (Alemazkoor et al., 2020). Hurricanes can result in customers being without power for weeks on end. For example, Figure 10 displays the number of customers without power in Calcasieu County, Louisiana, during Hurricane Laura, which made landfall in August 2020. Some customers experienced nearly a month without power.

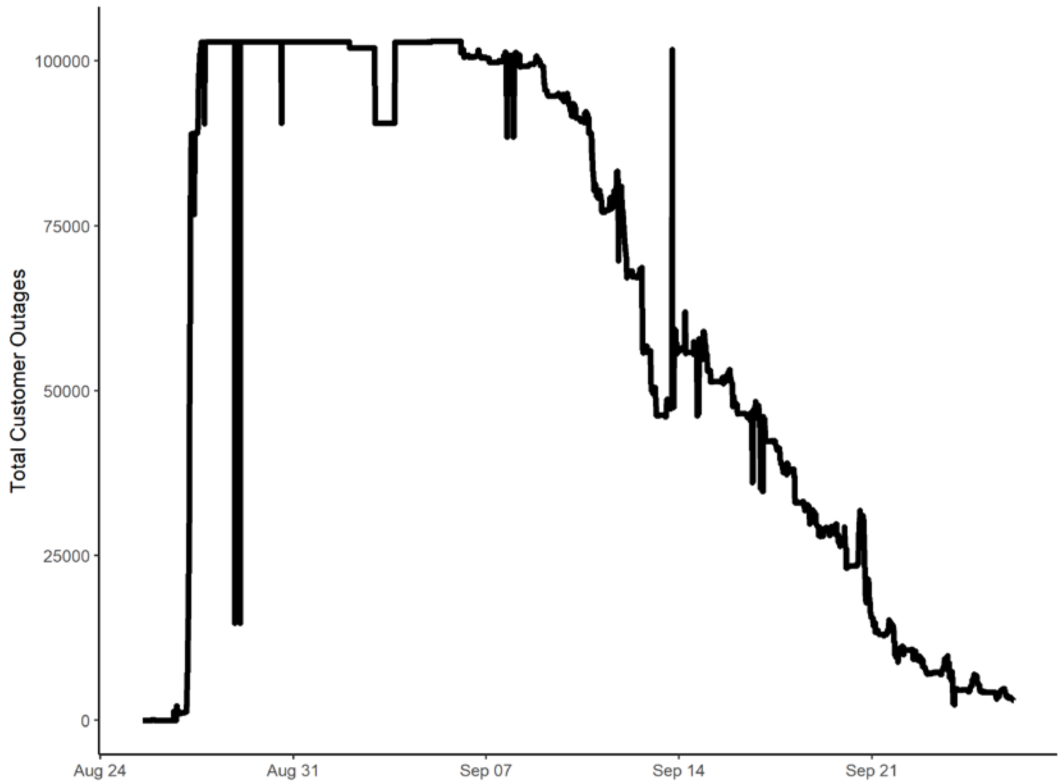


Figure 10. Customer outages in Calcasieu County, Louisiana, during Hurricane Laura

Table 11 presents the exceedance probabilities for major hurricane outages, and Table 12 presents the probability that a major hurricane outage duration will fall within a given duration interval. Major hurricane events are determined by any hurricane that is sufficiently damaging to be reported in a DOE emergency situation report. These results are based on the seven major hurricanes reported in Table 5. Thus, the duration probabilities reported are for a subset of major hurricanes to make landfall and cause widespread outages, not for all hurricane and tropical storm events.

Table 11. Outage Exceedance Probabilities for Major Hurricane Events[a]

Duration Hours (Days)	Exceedance Probabilities
12 (.5)	69.5%
24 (1)	52.0%
48 (2)	33.4%
72 (3)	19.4%
96 (4)	11.8%
120 (5)	6.5%
144 (6)	4.1%
168 (7)	2.5%
192 (8)	1.8%
216 (9)	1.5%
240 (10)	0.9%
264 (11)	0.8%
288 (12)	0.8%
312 (13)	0.8%
336 (14)	0.7%

Values were estimated from the seven hurricane events listed in Table 5.

Table 12. Probabilities a Major Hurricane Outage Duration Falls Within a Given Interval[a]

Interval	Probability
0–12 hours	30.5%
12–24 hours	17.4%
1–2 days	18.7%
2–3 days	13.9%
3–5 days	12.9%
5–7 days	4.0%
1–2 weeks	1.8%
>2 weeks	0.7%

Values were estimated from the seven hurricane events listed in Table 5.

7 Duration Estimates for Major Outages by Region

This section presents regional estimates of outage durations for major outage events. Major events are determined by outage events according to OE-417 events that impacted at least 10,000 customers. Figure 11 displays the exceedance probability curves for major events in the contiguous United States and for each region. The impact of hurricanes and tropical storms on outage durations clearly shows up in the higher average outage durations for the southern regions. Table 13 presents the same conditional exceedance probabilities for major outage events by region, and Table 14 displays the probabilities that a customer experiencing a major outage will experience an outage falling within a given duration band. Note that these values are not expected durations given that an outage occurs but instead expected durations given that the outage is a major outage event.

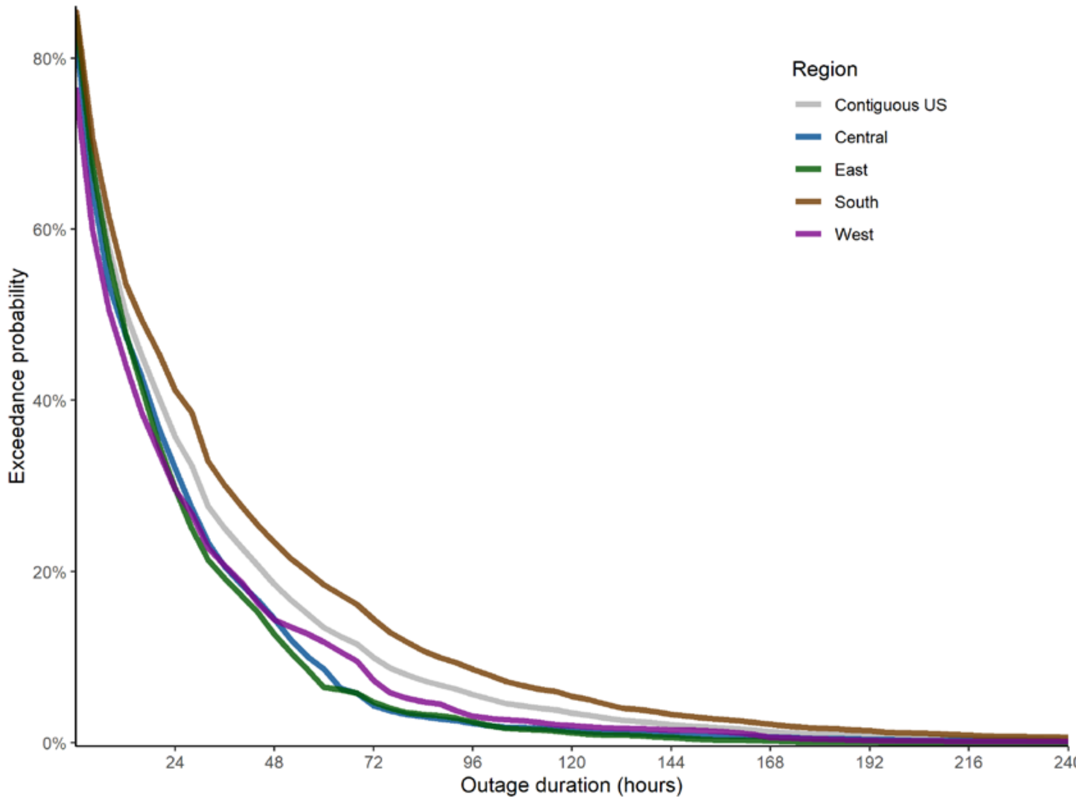


Figure 11. Exceedance probability curves by region

Table 13. Exceedance Probabilities for Major Outage Events by Region

Duration	Contiguous United States	Central	Eastern	Southern	Western
12 hours	50.3%	47.5%	47.8%	53.6%	44.2%
1 day	35.7%	32.0%	29.7%	41.2%	29.6%
2 days	18.5%	14.5%	12.7%	23.4%	14.4%
3 days	9.9%	4.3%	4.7%	14.4%	7.2%
4 days	5.6%	2.2%	2.4%	8.6%	3.1%
5 days	3.5%	1.4%	1.1%	5.4%	2.0%
6 days	2.1%	0.9%	0.7%	3.3%	1.5%
1 week	1.3%	0.7%	0.2%	2.2%	0.6%

Table 14. Probability Outage Duration Falls Within a Given Interval[a]

Interval	Contiguous United States	Central	Eastern	Southern	Western
0–12 hours	49.7%	52.5%	52.2%	46.4%	55.8%
12–24 hours	14.6%	15.5%	18.1%	12.4%	14.6%
1–2 days	17.2%	17.5%	17.0%	17.8%	15.2%
2–3 days	8.6%	10.2%	8.0%	9.0%	7.2%
3–4 days	4.3%	2.1%	2.3%	5.8%	4.1%
4–5 days	2.1%	0.8%	1.3%	3.2%	1.1%
5–6 days	1.4%	0.5%	0.4%	2.1%	0.5%
6–7 days	0.8%	0.2%	0.5%	1.1%	0.9%
>1 week	1.3%	0.7%	0.2%	2.2%	0.6%

[a] Values are for major outage events by region.

Nearly half of customers who experience a major outage event have power restored in less than 12 hours. There are significant differences in duration likelihoods by region given a major outage event. Outage events in southern states tend to have a higher likelihood than other regions of lasting multiple days, likely caused by the challenges of recovering power after hurricanes and tropical storms. The values are likely even more skewed for counties that are at a high risk of being impacted by tropical storms and hurricanes. Further research could analyze how outage duration probabilities vary with underlying hazards to provide more precise estimates for individual locations.

Although the results presented in Table 13 and Table 14 are valuable for determining the probability of outage durations given that a major event occurs, they do not tell us the likelihood that an event will occur. Because the EAGLE-I data do not have information on the total number customers in each county and do not cover all counties for all years, we cannot determine the outage duration likelihoods from the EAGLE-I data alone. To produce these estimates, we combined the EAGLE-I results with statistics from Form EIA-861, which provides information on outage duration averages. We assumed that non-MED event outages last less than 12 hours and that MED event outages are divided into smaller events that last less than 12 hours and larger events that have the distribution of outage durations estimated from the algorithm. We set the fraction of larger MED events to be such that the average outage duration given the outage distribution is equal to the EIA estimated CAIDI values during MED events.

Table 15 presents the estimated recurrence intervals—the average number of years between outage events—by region and duration interval. These values are centered on the CAIDI MED event average values for the years from 2013–2020. At least one outage event lasting between 0 and 12 hours is expected to occur each year. An outage event lasting between 1 day and 1 week is expected to occur between once every 24 years and once every 51 years, depending on the region, with a recurrence rate of once every 32 years across the contiguous United States.

Table 15. Recurrence Intervals for Outage Durations by Region[a]

	Contiguous	Central	Eastern	Southern	Western
0–12 hours	0.8	0.9	0.9	0.7	1.0
12–24 hours	67	58	34	44	84
1–2 days	59	48	37	34	78
2–3 days	127	87	77	74	203
3–5 days	152	229	167	68	186
5–7 days	495	1,112	675	191	1,152
>1 week	790	1,316	2,517	290	1,479

[a] Values are centered on average outage durations between 2013 and 2020. Values denote average years between events of a given duration.

The values presented are best estimates given the available data, and they provide a point of entry to resilience planning. Outage recurrence intervals and conditional probabilities can be direct inputs into probabilistic risk assessments of the benefits of resilience investments and can provide significant value to resilience analysis in general; however, the numbers presented here are estimated based on limited information and should not be taken as fact. Only a relatively short time frame of outage data was available for analysis.[19] Hazards vary drastically by location, meaning that the likelihood of an extended outage event at a given site might be much higher or lower than the average values described here. Additional work is required to better tie outage durations to the frequency of underlying hazards.

Estimates of the likelihood of multiday outages come with significant uncertainty. The relatively small time frame of available outage data combined with the low probabilities of multiday outages limits the accuracy of any estimates. Compounding the uncertainty is the fact that long-duration outages generally are caused by large-scale outage events, meaning that individual customer outage durations are not independent events. There are relatively few observations of long-duration outage events each year, and therefore they would require a very long time series to accurately estimate their likelihoods.

[19] A notable example is that Hurricane Sandy, which caused widespread extended outages in the Northeast, occurred before our analysis time frame and therefore was not included.

8 Summary and Conclusions

Extended power outages cause significant economic and societal impacts, and extreme weather and aging infrastructure are increasing their prevalence. Conducting cost-benefit analyses of resilience investments is important for determining which resilience investments to take to mitigate the impacts of power outages without investing in resilience solutions that are not cost-effective. Estimates of the frequency and duration of extended power outages are required for quantitative cost-benefit assessments of resilience investments, but there is currently a lack of publicly available data on extended power outages.

This report presents estimates of extended power outage duration frequencies and estimates of recurrence intervals for select outage duration intervals. We developed a methodology that allows us to estimate outage durations from customer outage data, which then allows us to estimate the outage statistics required for resilience planning and resilience cost-benefit analyses. Our methodology was applied to the EAGLE-I data set of county-level customer outage time series collected by ORNL, calibrated using California's PSPS outage data, and the values were calculated using extended outage events determined by DOE's emergency situation reports and DOE OE-417. To calculate the recurrence intervals, we combined estimates with average outage statistics provided by Form EIA-861.

Approximately one-third of customer outage durations for major outages exceed 24 hours, and approximately 1% exceed 1 week. These estimates vary by region, with southern states significantly more likely to experience extended outages than other states. A little more than 2% of all major power outages experienced between 2017 and 2021 in the southern United States lasted longer than 1 week, whereas this value is less than 1% for all other regions.

Shorter-duration power outages are relatively common, with customers experiencing on average more than one power outage each year lasting less than 12 hours. Longer-duration outages are less common but still significant, with customers experiencing an outage lasting more than 12 hours roughly once every 20 years and an outage lasting more than 24 hours roughly once every 30 years.

The frequency and duration of extended power outages are critical inputs in resilience planning and underpin any probabilistic approach to valuing the benefits of resilience investments. Therefore, this work contributes to quantitative resilience analysis; however, there is still significant work to be done. Future research can improve the accuracy of the estimates and determine how outage durations vary by underlying cause. Also, future power outages might have different characteristics than historical power outages, especially outages caused by the impacts of climate change. Coordination between utilities and researchers could greatly increase our understanding of outage durations and could generate additional insights, such as the type of customers and locations most at risk for outage events. Additional work could model changes in underlying hazards to determine how outage frequencies and durations will vary over time. Extended power outage events are inevitable, but understanding their causes, probabilities, and impacts are important steps to reducing the likelihood and consequences of extended power outages.

References

Alemazkoor, N., Rachunok, B., Chavas, D. R., Staid, A., Louhghalam, A., Nateghi, R., & Tootkaboni, M. (2020). Hurricane-induced power outage risk under climate change is primarily driven by the uncertainty in projections of future hurricane frequency. *Scientific Reports*, *10*(1), 1–9.

Consolidated Edison. (2013). *Storm Hardening and Resiliency Collaborative Report*. https://nescaum-dataservices-assets.s3.amazonaws.com/Storm-Hardening-and-Resiliency.pdf

DOE. (2020). *DOE-417 Electric Emergency Incident and Disturbance Report*. Department of Energy. https://www.oe.netl.doe.gov/Docs/OE417_Form_Instructions_05312024.pdf

DOE. (2022). *Electric Disturbance Events (OE-417) Annual Summaries*. https://www.oe.netl.doe.gov/OE417_annual_summary.aspx

Eaton. (2018). *Blackout Tracker: United States Annual Report 2017*. https://www.eaton.com/explore/c/us-blackout-tracker--2?x=NzOhds

EIA. (2021). *Annual Electric Power Industry Report, Form EIA-861*. https://www.eia.gov/electricity/data/eia861/

Ericson, S., & Lisell, L. (2020). A flexible framework for modeling customer damage functions for power outages. *Energy Systems*, *11*(1), 95–111. https://doi.org/10.1007/s12667-018-0314-8

Executive Office of the President. (2013). *Economic Benefits of Increasing Electric Grid Resilience to Weather Outages*. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwj1-4Xdgvn3AhXpc98KHT6hAFEQFnoECBUQAQ&url=https%3A%2F%2Fwww.energy.g

ov%2Fsites%2Fprod%2Ffiles%2F2013%2F08%2Ff2%2FGrid%2520Resiliency%2520Report_FINAL.pdf&usg=AOvVaw1AOKJI0ZRqzGiESwo3DY0e

FEMA. (2019). *BCA Toolkit* (6.0). https://www.fema.com/benefit-cost-analysis

FEMA. (2022). *Acquisition Benefit-Cost Analysis (BCA) Efficiencies for HMA Programs*. Federal Energy Management Agency. https://www.fema.gov/sites/default/files/documents/fema_rl-srl-acquisition-efficiency-methodology-report.pdf

Finster, M., Philips, J., & Wallace, K. (2016). *Front-Line Resilience Perspectives: The Electric Grid*. Argonne National Laboratory. https://www.energy.gov/sites/prod/files/2017/01/f34/Front-Line%20Resilience%20Perspectives%20The%20Electric%20Grid.pdf

Hanna, R., & Marqusee, J. (2022). Designing resilient decentralized energy systems: The importance of modeling extreme events and long-duration power outages. *IScience*, *25*(1), 103630. https://doi.org/10.1016/j.isci.2021.103630

Hotchkiss, E., & Dane, A. (2019). *Resilience Roadmap: A Collaborative Approach to Multi-Jurisdictional Resilience Planning*. National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy19osti/73509.pdf

Ji, C., Wei, Y., Mei, H., Calzada, J., Carey, M., Church, S., Hayes, T., Nugent, B., Stella, G., Wallace, M., White, J., & Wilcox, R. (2016). Large-scale data analysis of power grid resilience across multiple US service regions. *Nature Energy*, *1*(5), 1–8. https://doi.org/10.1038/nenergy.2016.52

Johnson, N., & Ma, Z. (2021). *Analysis of Loss-of-Offsite-Power Events 2020 Update* (INL/EXT-21-64151). Idaho National Laboratory. https://nrcoe.inl.gov/publicdocs/LOSP/loop-summary-update-2020.pdf

Kallay, J., Letendre, S., Woolf, T., Kwok, S., Hopkins, A., Broderick, R., Jeffers, R., Jones, K., & DeMenno, M. (2021). *Application of a Standard Approach to Benefit-Cost Analysis for Electric Grid Resilience Investments*. Sandia National Laboratories. https://www.synapse-energy.com/sites/default/files/Standard_Approach_to_Benefit-Cost_Analysis_for__Electric_Grid_Resilience_Investments_19-007.pdf

Karl, T., & Koss, W. (1984). Regional and national monthly, seasonal, and annual temperature weighted by area, 1895-1983. *Historical Climatology Series 4-3*.

Lacommare, K., Eto, J., Dunn, L., & Sohn, M. (2018). Improving the Estimated Cost of Sustained Power Interruptions to Electricity Customers. *Energy*, *153*. https://eta-publications.lbl.gov/sites/default/files/copi_26sept2018.pdf

Murphy, C., Hotchkiss, E., Anderson, K., Barrows, C., Cohen, S., Dalvi, S., Laws, N., Maguire, J., Stephen, G., & Wilson, E. (2020). *Adapting Existing Energy Planning, Simulation, and Operational Models for Resilience Analysis*. National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy20osti/74241.pdf

NARUC. (2019). *The Value of Resilience for Distributed Energy Resources: An Overview of Current Analytical Practices*. National Association of REgulatory Utility Commissioners. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjwhLnWo_v3AhU0p3IEHcykB2QQFnoECAUQAQ&url=https%3A%2F%2Fpubs.naruc.org%2Fpub%2F531AD059-9CC0-BAF6-127B-99BCB5F02198&usg=AOvVaw0eYkQHKacVBUbWR0oDZMXX

National Research Council. (2012). *Disaster Resilience: A National Imperative*. https://doi.org/10.17226/13457

NOAA. (2022). *Storm Event Database*. https://www.ncei.noaa.gov/pub/data/swdi/stormevents/csvfiles/

NREL. (2022). *Customer Damage Function Calculator* (1.0). cdfc.nrel.gov/

NYSERDA. (2014). *Microgrids for Critical Facility Resiliency in New York State*. http://nyssmartgrid.com/wp-content/uploads/Microgrids-for-Critical-Facility-NYS.pdf

PNNL. (2022). *Technical Resilience Navigator*. https://trn.pnnl.gov

Reidmiller, D. R., Avery, C. W., Easterling, D. R., Kunkel, K. E., Lewis, K. L. M., Maycock, T. K., & Stewart, B. C. (2018). *Impacts, Risks, and Adaptation in the United States: Fourth National Climate Assessment, Volume II*. U.S. Global Change Research Program. nca2018.globalchange.gov

Sanstad, A., Zhu, Q., Leibowicz, B., Larsen, P., & Eto, J. (2020). *Case Studies of the Economic Impacts of Power Interruptions and Damage to Electricity System Infrastructure from Extreme Events*. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwiD3Yy04_n3AhXyTN8KHSirD0IQFnoECAYQAQ&url=https%3A%2F%2Femp.lbl.gov%2Fpublications%2Fcase-studies-economic-impacts-power&usg=AOvVaw3zwqJ-ZAQCph5hoo3X34zf

Silverstein, A., Gramlich, R., & Goggin, M. (2018). *A Customer-focused Framework for Electric System Resilience*. Grid Strategies. https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&cad=rja&uact=8&ved=2ahUKEwjUmZP0p_33AhW3gXIEHd2eDSgQFnoECAUQAQ&url=https%3A

%2F%2Fmedia.rff.org%2Fdocuments%2FRFF20R20Street20Resilience20Workshop20Silverstein20Slides.pdf&usg=AOvVaw0-fW9DxiCdxXNlvNZyXM6C

Warren, C., Bouford, J., Christie, R., Kowalewski, D., McDaniel, J., Robinson, R., Schepers, D., Viglietta, J., & Williams, C. (2001). Classification of Major Event Days. *IEEE*. https://cmte.ieee.org/pes-drwg/wp-content/uploads/sites/61/2003-01-Major-Events-Classification-v3.pdf

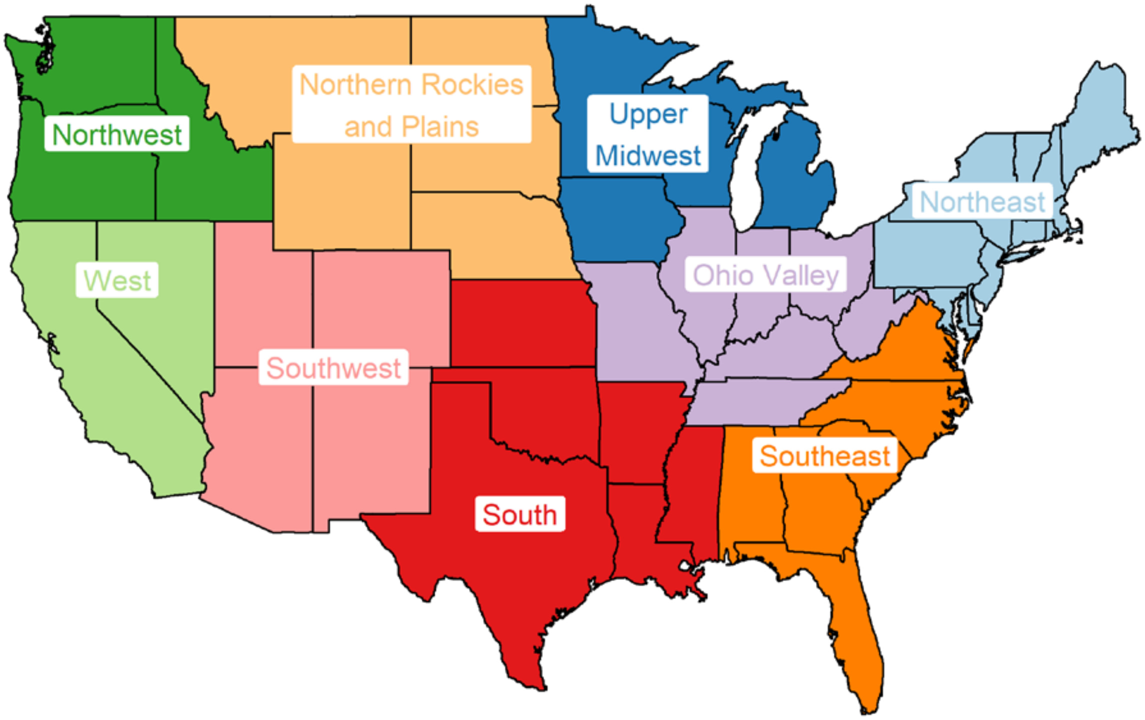
Willis, H., & Kia, K. (2015). *Measuring the Resilience of Energy Distribution Systems*. Rand Corporation. https://www.rand.org/pubs/research_reports/RR883.html

Zamuda, C., Larsen, P., Collins, M., Bieler, S., & Schellenberg, J. (2019). Monetization methods for evaluating investments in electricity system resilience to extreme weather and climate change. *The Electricity Journal*, *32*(106641), 1–7.

Zuzak, C., Mowrer, M., Goodenough, E., Burns, J., Ranalli, N., & Rozelle, J. (2022). The national risk index: Establishing a nationwide baseline for natural hazard risk in the US. *Natural Hazards*, 1–25.

Appendix A. Estimates by Climate Region

Scientists at the National Centers for Environmental Information identified nine climactically consistent regions (Karl and Koss 1984). Because of the impact of weather on outages, climate regions provide a natural grouping. Figure A-1 displays the climate regions, and the corresponding table provides the land area and population for each region. Outage estimates by climate regions are also used in the National Renewable Energy Laboratory's (NREL) Customer Damage Function (CDF) Calculator, which can be accessed at https://cdfc.nrel.gov/.



Region	States	Land Area (Mi^2)	Population (Million)
Northeast	CT, DE, ME, MD, NH, NJ, NY, PA, RI, VT	174,000	64
Northern Rockies and Plains	MT, NE, ND, SD, WY	464,000	5
Northwest	ID, OR, WA	245,000	14
Ohio Valley	IL, IN, KY, MI, OH, TN, WV	306,000	51
South	AR, KS, LA, MI, OK, TX	555,000	47
Southeast	AL, FL, GA, NC, SC, VA	281,000	63
Southwest	AZ, CO, NM, UT	421,000	19
Upper Midwest	IA, MI, MN, WI	247,000	25
West	CA, NV	266,000	42

Figure A-1. U.S. climate regions

Table A-1 provides the exceedance probabilities for each climate region, Table A-2 provides the probability intervals and recurrence intervals, and Table A-3 provides recurrence intervals by climate region. The recurrence intervals are determined by combining Environment for Analysis of Geo-Located Energy Information (EAGLE-I) results with utility System Average Interruption Duration Index (SAIFI) and Customer Average Interruption Duration Index (CAIDI) information using the process described in the main text of the report. The Southwest region did not have any tracked outages longer than 3 days, and therefore it does not have a recurrence interval for longer-duration outages.

Table A-1. Exceedance Probabilities by Climate Region

Region	12 Hours	1 Day	3 Days	5 Days	1 Week
Northeast	51.4%	33.4%	5.4%	1.1%	0.3%
Upper Midwest	56.4%	40.7%	5.4%	2.2%	1.2%
Ohio Valley	32.6%	18.0%	3.4%	1.1%	0.1%
Southeast	58.4%	43.1%	14.8%	6.5%	2.3%
Northern Rockies and Plains	48.4%	22.6%	3.8%	0.4%	0.04%
South	44.8%	35.5%	12.1%	3.1%	1.7%
Southwest	26.7%	0.2%	0.02%	0.01%	0.00%
Northwest	44.8%	25.9%	8.2%	3.9%	1.0%
West	44.7%	32.2%	7.2%	1.3%	0.5%

Table A-2. Probability Intervals by Climate Region

Region	0–12 Hours	12–24 Hours	1–2 Days	2–3 Days	3–5 Days	5–7 Days	>1 Week
Northeast	40.0%	21.3%	20.4%	11.8%	5.1%	1.0%	0.4%
Northern Rockies and Plains	37.1%	35.1%	9.6%	13.2%	4.4%	0.5%	0.04%
Northwest	44.6%	25.4%	16.5%	4.4%	5.1%	2.4%	1.8%
Ohio Valley	59.6%	18.4%	13.2%	4.3%	3.3%	1.1%	0.1%
South	49.5%	12.2%	13.7%	10.0%	11.2%	1.7%	1.7%
Southeast	32.6%	18.7%	24.4%	8.3%	8.9%	4.6%	2.6%
Southwest	63.9%	35.8%	0.4%	0.01%	0.02%	0.01%	0.00%
Upper Midwest	38.1%	16.3%	24.5%	13.9%	4.8%	1.2%	1.2%
West	51.0%	12.1%	18.8%	8.1%	8.6%	0.7%	0.6%

Table A-3. Recurrence Intervals by Climate Region

Region	0–12 Hours	12–24 Hours	1–2 Days	2–3 Days	3–5 Days	5–7 Days	>1 Week
Northeast	0.9	33	35	61	139	701	1,880
Northern Rockies and Plains	0.9	60	218	159	475	4,339	>10,000
Northwest	0.9	34	52	198	169	353	488
Ohio Valley	0.8	46	65	198	260	781	7,874
South	0.6	63	57	77	70	452	450
Southeast	0.7	32	25	72	68	133	233
Southwest	1.0	31	3,157	>10,000			
Upper Midwest	0.9	49	32	57	165	668	647

Table A-4 displays the recurrence intervals used in NREL's CDF Calculator.

Table A-4. Outage Duration Estimates Integrated into NREL's CDF Calculator[a]

Region	5 Minutes–1 Hour	1–4 Hours	4–8 Hours	8–24 Hours	1 day–1 week	>1 Week
Contiguous United States	1.11	3.3	72	42	30	790
Northeast	1.30	3.9	48	22	19	1880
Northern Rockies and Plains	1.14	3.4	146	47	76	10,000*
Northwest	1.19	3.6	43	22	30	488
Ohio Valley	1.07	3.2	32	26	39	7,874
South	0.82	2.5	39	35	21	450
Southeast	1.00	3.0	49	22	13	233
Southwest	1.42	4.3	44	20	2,835	10,000*
Upper Midwest	1.28	3.9	58	31	18	647

[a] The recurrence intervals that exceeded 1 event every 10,000 years were replaced by a recurrence interval of 1 in 10,0000.