International Journal of Disaster Risk Reduction 133 (2026) 105980

Contents lists available at ScienceDirect

International Journal of Disaster Risk Reduction

journal homepage: www.elsevier.com/locate/ijdrr

Revealing growing and disparate vulnerability in the U.S. power system: A spatiotemporal analysis of nationwide outages from 2014 to 2023

Bo Li [a,*], Junwei Ma [a], Olufemi A. Omitaomu [b], Ali Mostafavi [a]

[a] Urban Resilience.AI Lab, Zachry Department of Civil and Environmental Engineering, Texas A&M University, College Station, TX, United States
[b] Oak Ridge National Laboratory, Oak Ridge, TN, United States

ARTICLE INFO

Keywords:
Power outage
Power system vulnerability
Energy justice
Power system reliability
Spatiotemporal analysis
Power system resilience

ABSTRACT

Power systems are increasingly challenged by a range of external and internal threats that undermine their reliability and resilience. Power system vulnerability, the proneness of the power system to disruptions, can be empirically characterized through the observable manifestations of power outages. However, existing research remains limited in spatial coverage, temporal scope, and analytical consistency, and lacks comprehensive, longitudinal, large-scale, and fine-grained analyses to capture the spatiotemporal dynamics of vulnerability. Recognizing this, we analyzed 179,053,397 county-level power outage records with a 15-min interval across 3,022 US counties during 2014–2023. Applying a framework encompassing frequency, duration and intensity, we systematically assessed the dynamics of U.S. power system vulnerability. Results reveal an escalating trend over the past decade, with outages becoming more frequent, prolonged, and intense. Nationally, cumulative customer outage time reached 7.86 billion customer-hours, with a median of 0.64 million per-county over the past decade, underscoring significant service disruptions. Coastal regions, especially in California, Florida, and New Jersey, experienced more frequent and longer outages, while some inland areas exhibited higher outage intensity relative to their customer base. Moreover, we observed a strengthening association between social vulnerability and outage metrics over time, indicating that counties with higher social vulnerability experienced more severe and frequent outages, creating "dual-burden" regions where social disadvantage and infrastructural vulnerability compound each other. These findings provide a nationwide and longitudinal characterization of power system vulnerability in the U.S., offering empirical insights to inform practitioners in prioritizing investments for a more reliable, resilient and equitable energy infrastructure.

1. Introduction

Power systems are increasingly exposed to a complex interplay of external stressors and internal weaknesses that challenge their reliable operation. In recent decades, the growing frequency and intensity of climate-related extremes, such as hurricanes, wildfires, and winter storms, have imposed unprecedented stress on transmission and distribution infrastructures, causing widespread service disruptions. For example, Winter Storm Uri (2021) left more than 4.5 million people in Texas without electricity, as freezing

* Corresponding author.
E-mail address: libo@tamu.edu (B. Li).

https://doi.org/10.1016/j.ijdrr.2025.105980
Received 27 June 2025; Received in revised form 31 October 2025; Accepted 20 December 2025
Available online 23 December 2025

temperatures paralyzed natural gas supply lines, froze wind turbines, and forced numerous power plants offline, revealing deep vulnerabilities in both generation and grid preparedness [1]. Similarly, Hurricane Ian, which made landfall in southwest Florida in September 2022 with sustained winds exceeding 150mph [2], severely damaged power infrastructures and left approximately 2.7 million customers without electricity at its peak [3].

While such external shocks expose the acute stress that climate extremes impose on the grid, internal factors further exacerbate systemic fragility even in the absence of major disasters. Across many regions, power infrastructures are aging, with a large share of transmission lines, transformers, and substations operating well beyond their intended design life and under deferred maintenance regimes. Recent assessments indicate that nearly 70 % of U.S. transmission lines and transformers are more than 25 years old, and many assets built in the 1960s–1970s are approaching or exceeding their 50-year service life [4]. Deferred maintenance and under-investment in modernization have created significant backlogs of critical upgrades, leaving deteriorating equipment more prone to operational failures [5]. The convergence of internal deficiencies and external hazards create compound stressors to the power systems. Therefore, it is essential to develop a systemic understanding on the power system vulnerability, which refers to the proneness of power system to disruptions [6]. Here, we employ power outage as an observable manifestation and practical, scalable indicators of this vulnerability.

Despite increasing recognition of these challenges, empirical understanding of power system vulnerability remains fragmented and event-specific. Most existing studies focus on individual blackout events or specific hazard types, offering valuable but localized insights into outage behavior. For example, investigations of Hurricane Isaac in Louisiana and Winter Storm Uri in Texas have revealed important patterns in outage distribution, duration, and restoration dynamics under extreme conditions, but their findings are confined to single events and limited in temporal scope [7–9]. Some research has focused on outages driven by specific hazards at regional scales, such as those induced by wildfires and extreme weather events, revealing how different hazard types disrupt power system performance and prolong restoration processes [10–12]. Although these regional studies broaden understanding beyond single events, they remain spatially limited and short-term, constraining their ability to reveal long-term or nationwide patterns. Furthermore, Do et al. characterized the spatiotemporal distribution of power outages, but focused only on weather event related outages and a short study period (2018–2020) [13]. Ankit et al. conducted a nationwide analysis on U.S. power outages from 2002 to 2019, yet their assessment excludes small blackouts and aggregated at the state scale [14]. These efforts have characterized specific aspects of outage behavior under distinct hazard contexts. However, comprehensive, longitudinal, large-scale and fine-granular analyses remain lacking to capture the spatiotemporal dynamics of power system vulnerability.

To address this limitation, a consistent and scalable approach is needed to quantify and compare outage characteristics across space

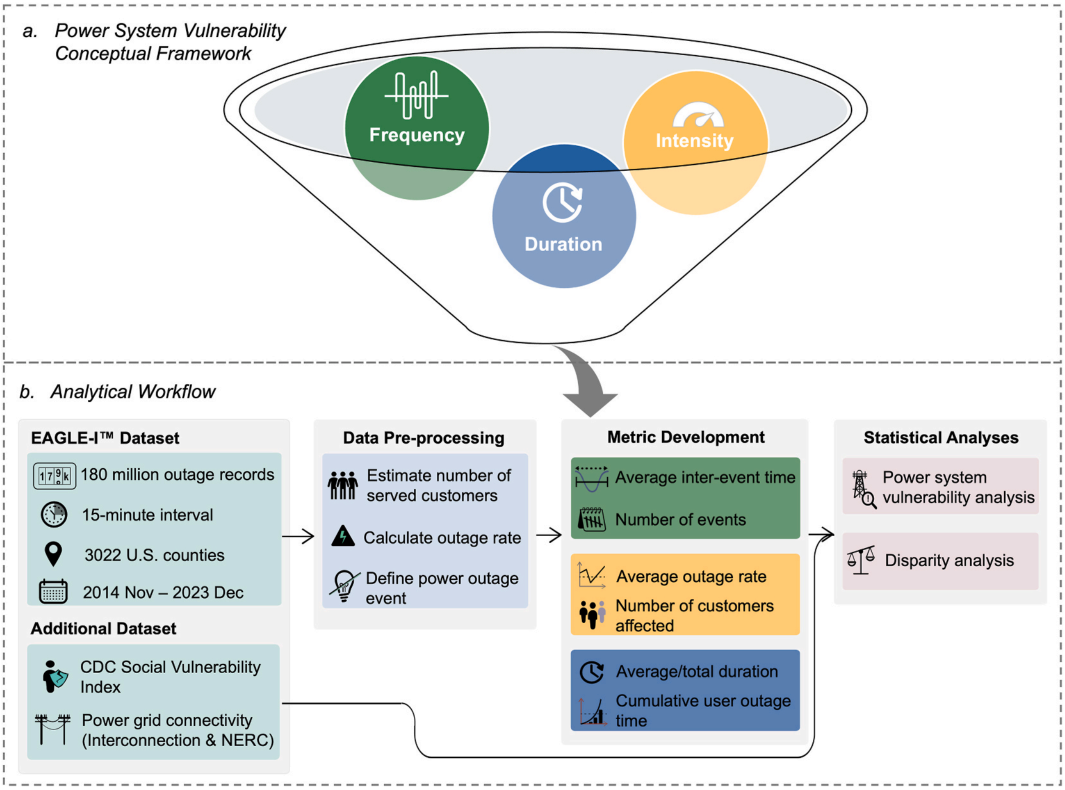

Fig. 1. Power system vulnerability assessment metrics. We assessed power system vulnerability from the three dimensions—frequency, duration, and intensity—and developed metrics for each dimension. See Methods for metrics definition.

and time. Previous studies have proposed various indicators to describe outage behavior, yet these measures differ widely in scope and interpretation. Traditional reliability metrics, such as the system average interruption duration index (SAIDI) and system average interruption frequency index (SAIFI) are widely used by utilities and regulators to assess system performance. While these indicators provide valuable summaries of overall system-wide service reliability, they are typically aggregated at the utility scale and exclude major events, thereby limiting their capability to reveal spatial and temporal variability in outage patterns [15–17]. Beyond those standard indices, the literature has also employed metrics such as event-specific impact measures, component failure rates (e.g. Refs. [18,19]) to capture different aspects of power system performance. While these metrics provide valuable insights, they vary considerably in definition, scope and applicability, which complicates systematic comparison across regions and time periods.

Building on these existing efforts, this study establishes a coherent and scalable framework to characterize power system vulnerability through the observable power outage characteristics. The framework incorporates three complementary dimensions, frequency, duration and intensity, to capture the distinct aspects of complex, multifaceted power system performance, describing the recurrence, persistence and magnitude of power system disruptions (Fig. 1). The multi-dimensional perspective is critical, as outages with different temporal and intensity profiles can impose different consequences on communities and industries. For example, long-duration outages can threaten public health, compromise critical infrastructure services, and cause severe economic losses across regions, while frequency short outages, though brief, can disrupt telecommunication and digital payment systems, delay emergency response systems, and damage sensitive medical and industrial equipment. This approach also aligns with recent analytical frameworks (e.g. Refs. [20,21]), which employs these three dimensions to enable a more nuanced understanding of system performance under stress.

Following this framework, we applied a large-scale, longitudinal, and high-spatiotemporal-resolution power outage dataset [22] to capture the dynamics of power system vulnerability in the U.S. Specifically, we analyzed 179,053,397 historical power outage records across 3,022 counties at 15-min temporal resolution from November 2014 through December 2023, obtaining from the Environment for Analysis of Geo-Located Energy Information (EAGLE-I™) platform [23]. For each of the three dimensions, frequency, duration and intensity, we developed multiple quantitative metrics to capture power outage characteristics. Using those metrics, we conducted spatiotemporal and disparity analyses to examine the spatial patterns, evolving trends and variations in power system vulnerability across regions and population groups, providing a comprehensive assessment of the dynamics and inequities of the U.S. power system vulnerability.

This study reveals several important insights into the trends and characteristics of power system vulnerability in the United States. The results provide robust empirical evidence on the extent, spatial variation, and temporal escalation of these vulnerabilities. Analysis on high-resolution and large-scale power outage data indicates that significant and widespread disruptions have occurred across the U. S. power system. The observed disruptions exhibit distinct spatial patterns, with coastal regions experience more frequent and prolonged outages than inland areas. Moreover, a worsening temporal trend is observed, with outages increasing in frequency and severity over the past decades, underscoring the growing vulnerability of the U.S. power system. Further analysis reveals that social challenges and power system challenges intersect, as counties with higher social vulnerability experience more frequent, longer, and larger-scale outages, creating "dual-burden" regions, where social disadvantages and infrastructural fragility compound each other. These insights are crucial for power infrastructure owners and operators, policymakers, and community leaders as they develop policies and implement strategies aimed at prioritizing infrastructure and optimizing resource allocation to enhance power systems resilience and reliability.

2. Methods

2.1. Power outage data

The source of power outage information is the Environment for Analysis of Geo-Located Energy Information (EAGLE-I™) dataset. EAGLE-I™ is a geographic information system and data visualization platform developed by Oak Ridge National Laboratory (ORNL) to map populations experiencing electricity outages every 15 minutes at the county level in the United States [24]. The dataset is compiled using a variety of web parsing techniques to systematically collect near real-time outage information from several hundred large electric utilities and utility conglomerates across the U.S., which report outages from their respective collections of electric utilities [22]. The EAGLE-I™ outage data represents approximately 90 % of utility customers nationally [22].

The core dataset used in this study includes ten years of validated historic EAGLE-I™ records, encompassing county-level power outage information from November 2014 through December 2023 at 15-min intervals. This dataset covers 3,022 counties in the contiguous United States (CONUS), representing 96.15 % of the CONUS population. The data is publicly available at https://doi.org/10.1038/s41597-024-03095-5.

The EAGLE-I™ dataset reports the estimated number of customers experiencing an outage at 15-min intervals for all counties in the CONUS. However, the total number of customers by county is not consistently available across all years. To ensure a geographically consistent measure of outages, we generated annual estimates of total customers for each county. First, we performed a linear extrapolation to estimate state-level total customer counts for 2014–2016, using the 2017–2021 state-level data provided by ORNL. Next, we used the available county-level customer data for 2022 and 2023 to determine each county's typical proportion of customers within its state. In this process, we calculated, each county i in state s, its share of total state customers for both 2022 and 2023 as Equation (1):

$$Share\ i,s,y = \frac{Customers\ i,s,y}{Total\ Customers\ s,y} \tag{1}$$

where $y\ = 2022\ or\ 2023$. We then averaged these two annual shares for each county to obtain a stable average share value (Equation (2)):

$$Average\ Share\ i,s = \frac{Share\ i,s,2022 + Share\ i,s\ 2023}{2} \tag{2}$$

This average share was assumed to represent each county's typical proportion of customers within the state and was multiplied by the state's total customer count for earlier years (2014–2021) to estimate its county-level customer numbers.,

It is important to note that the customers in our study cannot be directly translated to the population. Electricity utilities define “customers” in various ways, typically referring to an electric meter, a building, or a facility. In residential areas, a customer might be a household, while in commercial areas, a customer could be a business or a facility.

2.2. Power outage metrics

To identify a county as experiencing an outage, we first calculated the power outage rate every 15 minutes. The power outage rate is defined as the ratio of the number of customers without power to the total number of customers in a county (Equation (3)). This metric accounts for the total number of customers in a county and enables us to compare outage counts across counties with varying customer sizes.

$$Power\ Outage\ Rate = \frac{Number\ of\ customers\ without\ power}{Total\ number\ of\ customers} \tag{3}$$

where the number of customers without power refers to the number of customers experiencing an outage at 15-min intervals, and the total number of customers represents the estimated total number of customers in the county.

We then defined a power outage event as continuously occurring whenever the power outage rate met or exceeded 0.1 % based on the previous studies [13,25]. This threshold helps distinguish true power outages from other issues, such as service disconnections due to non-payment [26]. We screened out the 15-min power outage records where the power outage rate was smaller than 0.1 % and greater than 100 % and identified a total of 3,022,915 power outage events across 3,022 counties over the 10-year period.

To better characterize these power outage events, we developed a power outage vulnerability assessment model based on the environmental exposure model [20,21,27], including the dimensions of frequency, duration, and intensity. Standard indices, such as system average interruption frequency (SAIFI) and system average interruption duration index (SAIDI) are not used in this study, because they are typically defined for annual, utility-level performance assessed based on detailed service-log data [16]. Instead, we constructed county-level frequency, duration and intensity metrics that conceptually aligned with those standard indices but adapted for spatially consistent, nationwide analysis (Fig. 1). These metrics provide a comprehensive framework for assessing power outage vulnerabilities and quantifying their impacts over time and across different regions.

- **Number of events**: this metric counts the total number of power outage events per year at the county level, measuring frequency of power outages.
- **Average outage rate**: this metric calculates the average power outage rate for all power outage events per year at the county level, focusing on the intensity of power outages.
- **Average/total duration**: this metric computes both the average and total duration of all power outage events per year at the county level, assessing the duration of power outages.
- **Average inter-event time**: this metric measures the average time interval between power outage events per year at the county level, assessing the frequency of power outages.
- **Number of customers affected**: this metric counts the cumulative number of customers who experienced power outages in each county per year. To provide a more complete picture, we also calculated the peak number of customers affected across all the power outage events per year at the county level. These metrics assess the intensity of power outages.
- **Cumulative customer outage time**: this metric is calculated by multiplying the number of customers without power by the corresponding outage duration in a county across all power outage records per year. It measures both intensity and duration of power outages.

2.3. Socio-economic data

2.3.1. Urban and rural classification

Urban and rural classification is commonly used to assess socioeconomic development differences at the U.S. county level [28,29]. In our study, counties are categorized as either “urban” or “rural” according to the 2013 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme [30]. NCHS has developed a six-level urban-rural classification scheme for U.S. counties and county-equivalent entities. We designate counties as urban (981 counties) if they fall into the three most urban categories: large central metropolitan, large fringe metropolitan, and medium metropolitan. Counties are classified as rural (2050 counties) if they fall into the three least urban categories: small metropolitan, micropolitan, and noncore.

2.3.2. Social vulnerability index

Socially disadvantaged communities often face greater challenges in preparing for, coping with, and recovering from power outages, and therefore may experience greater impacts from vulnerable power systems and require additional support during disruptions [31,32]. To identify socially vulnerable areas, we used the Social Vulnerability Index (SVI) developed by the U.S. Centers for Disease Control and the Agency for Toxic Substances and Disease Registry (CDC/ATSDR) [33]. The SVI is based on 16 census variables from the American Community Survey, encompassing socioeconomic status, household characterization, racial and ethnic minority status, as well as housing type and transportation. Variables include poverty (150 % below the U.S. Department of Health and Human services poverty guidelines), unemployment, housing cost burden, education attainment, health insurance coverage, age composition (aged 65 and older or aged 17 and younger), disability status, single-parent households, English language proficiency, racial and ethnic minority status, housing type (multi-unit structures or mobile homes), crowding, vehicle access, and group quarters. The SVI ranges from 0 to 1, where values closer to 0 represent lower vulnerability and values closer to 1 indicate higher social vulnerability.

The SVI has been widely employed in power outage research as a standardized indicator of social disadvantages. For example, Guikema et al. employed the SVI as an explanatory variable in a random forest model to assess how social disadvantage aligns with areas of heightened tropical cyclone-induced outage risks [34]. Similarly, Flores et al. used the SVI to examine associations between social vulnerability and severe outage experiences during the 2021 Texas winter storm [9], while Nejat et al. (2022) drew conceptually from the SVI framework by using its core socioeconomic, housing, and demographic components to examine outage disparities [35]. Tormos-Aponte et al. adapted the index to create the Puerto Rico Social Vulnerability Index, retaining the same categorical structure but modifying variables such as language and minority indicators to fit local demographics [36]. We acknowledged that the SVI has certain limitations, as it does not capture the full complexity of social dependence on electricity or include outage-specific factors, such as the needs of individuals who rely on electricity for medical equipment [37,38]. Nevertheless, it offers a standardized and nationally consistent measure of structural social disadvantages across U.S. counties, making it well-suited for integration with our nationwide, large-scale power outage dataset at the county level. Therefore, we use the SVI in this study as an appropriate and reliable proxy for assessing disparities in power system vulnerabilities.

2.4. Power grid connectivity data

Regional differences in power infrastructure vulnerability can be influenced by large-scale grid topology. To investigate whether

Fig. 2. Six metrics of county-level power outage data from 2014 to 2023. a. Number of outage events; b. Average outage rate; c. Total duration; d. Average inter-event time; e. Number of customers affected; f. Cumulative customer outage time. Maps display the spatial distribution of ten-year summarizing statistics of the metrics. Plots on the bottom right corner of the maps show statistical distributions. The lollipop plots on the right side of each sub-figure show the metric year by year. Maps include 3022 counties, with gray areas indicating counties without data.

grid connectivity scenarios impact the vulnerability characteristics of power infrastructure, we collected data on two major types of grid connectivity: interconnections power grids [39] and the North American Electric Reliability Corporation (NERC) [40]. The detailed data description and results are presented in Supplementary Information.

2.5. Statistical analysis

The power law distribution is often used to model scenarios where a small number of events are common, while a large number of events are rare but significant [41]. Previous research indicates power law behaviors are prevalent in blackout events [42,43]. Consequently, we applied the power law model to analyze whether it could shed light on the distribution of time intervals between successive power outage events. The power law distribution in our study is defined by Equation (4):

$$P(x) \sim x^{-\alpha} \tag{4}$$

where $P(x)$ is the probability of observing an inter-event time x, and α is the exponent of the power law. The probability decreases as x increases, with the rate of decrease determined by α. We divided county-level average inter-event time into two groups (2014–2018 and 2019–2023), and then checked the fitness of power law distribution for each group (Fig. 5e).

We employed an ordinary least squares (OLS) regression model (Equation (5)) to capture the relationships between the social vulnerability index and power outage metrics (outage duration, outage rate, inter-event time, and number of events) at the county level for the two-years groups (Fig. 6).

$$y_i \sim \beta_0 + \beta_1 x_i + \varepsilon_i \tag{5}$$

where, y_i is the power outage metric of county i; x_i is the social vulnerability index of county i; β are coefficients; and ε_i is the error term.

We also utilized several statistical tests to assess the significance. First, we used the paired Wilcoxon test, a non-parametric method for comparing paired observations, to analyze the box plots of the average outage rates for the 2014–2018 and 2019–2023 groups (Fig. 4a). Second, we used the Kolmogorov-Smirnov test to compare the empirical distribution with the fitted power law model (Fig. 5e), where a smaller K-S statistic indicates a better fit. Third, the Kruskal-Wallis H test was employed to determine the significance of differences among the five two-year groups of power outage metrics shown in Fig. 8. This test assesses whether there are statistically significant differences among three or more independent groups. Finally, we applied the Mann-Whitney U test to evaluate differences between the distributions of two independent groups: the 2014–2018 and 2019–2023 duration proportion groups (Fig. 3b) and the urban and rural groups (Fig. 9). All analyses were conducted using Python, and the 2019 TIGER/Line US County Shapefiles were

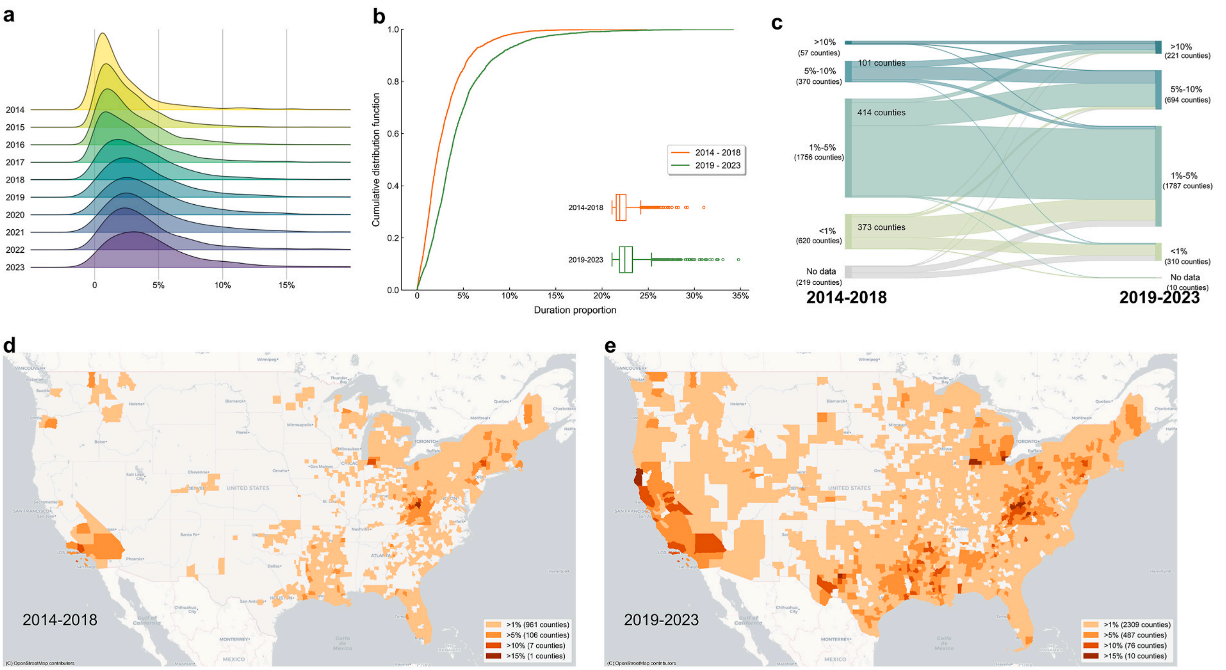

Fig. 3. Descriptive statistics of power outage duration. a. Probability density plots of year-by-year outage duration proportion; b. Distribution plots of outage duration for US counties during the period 2014–2018 (n = 2803) and the period 2019–2023 (n = 3012). The curves show the cumulative distribution function. The Mann-Whitney U test was performed to examine group differences ($p < 0.05$); c. Sankey plot displaying how the outage proportion changes over the ten years for each county; d. Spatial distribution of hotspots with repetitively prolonged power outages during 2014–2018. e. Spatial distribution of hotspots with repetitively prolonged power outages during 2019–2023.

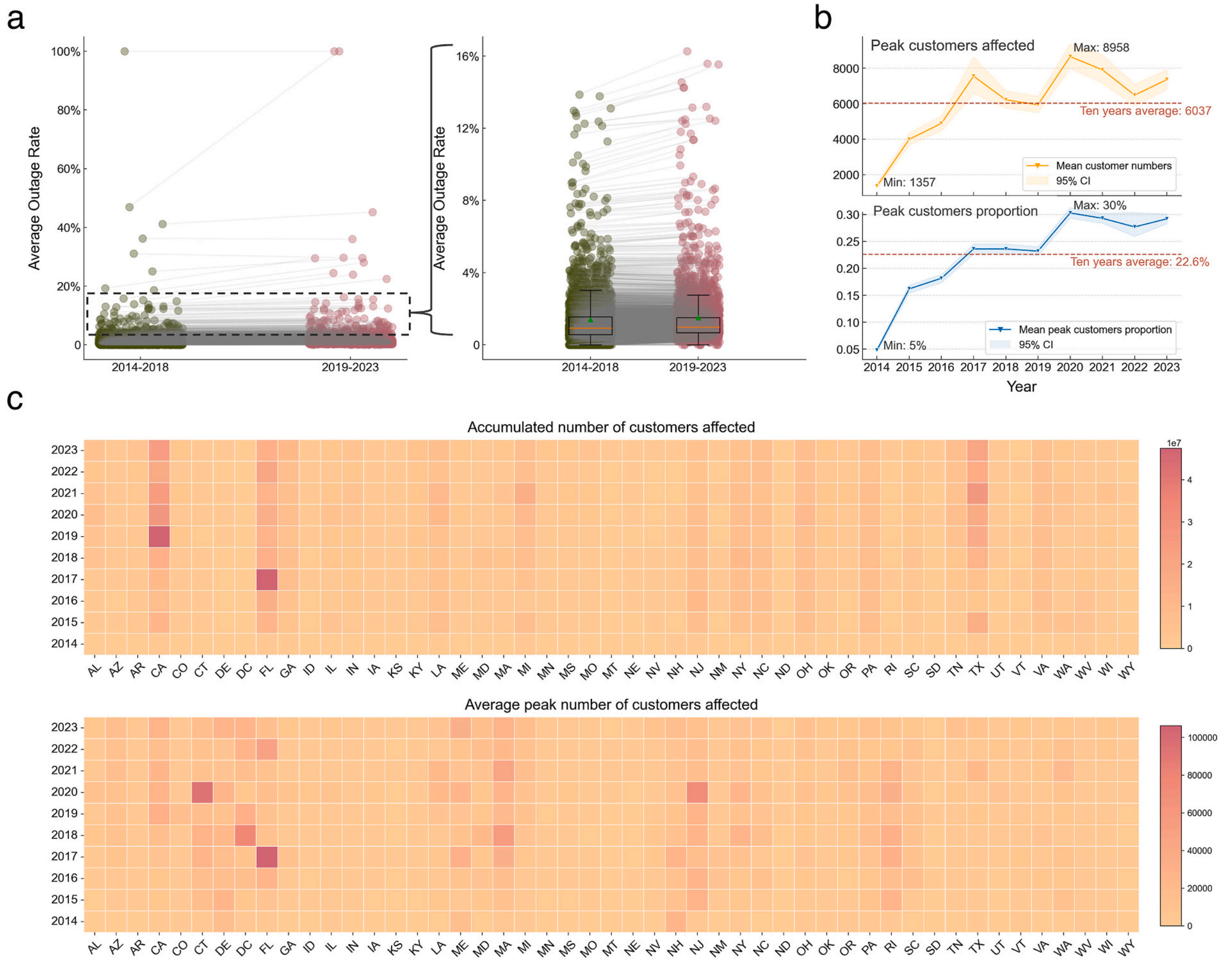

Fig. 4. Descriptive statistics on power outage intensity. a. The line-linked paired points represent the average power outage rate of counties in the same position during 2014–2018 and 2019–2023 periods, respectively. Plots with average outage rate in the range (0 %, 16 %) are zoomed in. The 2019–2023 outage rate is significantly higher than that of 2014–2018 (Paired Wilcoxon test, $p < 0.05$), indicating an upward trend in the average outage rate. Boxplot shows the distribution of outage rate values, with a median line, mean triangle, and box ends representing first and third quantiles. Whiskers extend to values within 1.5 times the interquartile range. b. Line plots for the peak number of affected customers by year. The upper plot shows the absolute number of affected customers (defined as the maximum number of customers impacted across all recorded outage events in each year, aggregated at the county level), while the lower plot shows the relative proportion of affected customers with respect to the total number of covered customers (i.e. data coverage, which remained nearly constant during the study period). Maximum and minimum values are denoted. The shaded area shows a 95 % confidence interval of the line plot. Together, both plots demonstrate a clear upward trend in outage magnitude and relative impact, confirming that the observed escalation reflects intensification of outage event rather the changes in data coverage. **c.** Heatmap for the number of affected customers. The X-axis shows the US states.

utilized to create the nationwide maps for this study [44].

3. Results

3.1. Overall spatiotemporal trends of power outages in the U.S. from 2014 to 2023

This study first summarized the statistics of six power outage metrics spanning from November 2014 to December 2023 in 3,022 counties of the contiguous United States (CONUS) (Table 1). Across the study period, U.S. counties experienced 999.4 power outage events on average (IQR: 486.25, 1,369; max: 5,761). The average total power outage duration over ten years is 118.79 days (IQR: 53.61, 155.90; max: 890.25), meaning that, on average across all counties in the CONUS, power outage accounted for 3.65 % (IQR: 1.71 %, 4.69 %; max: 25.96 %) of the total time during the past decade. The average interval between power outage events is 7.16 days (IQR: 2.22, 5.71; median: 3.37), indicating that the counties experienced a power outage event approximately every week. The mean power outage rate is 1.51 % (IQR: 0.70 %, 1.54 %; median: 1.02 %). Over the past ten years, power outage events cumulatively affected a mean of 540,915 customers in each county (IQR: 61,962, 486,026; median: 191,557), indicating a substantial and widespread

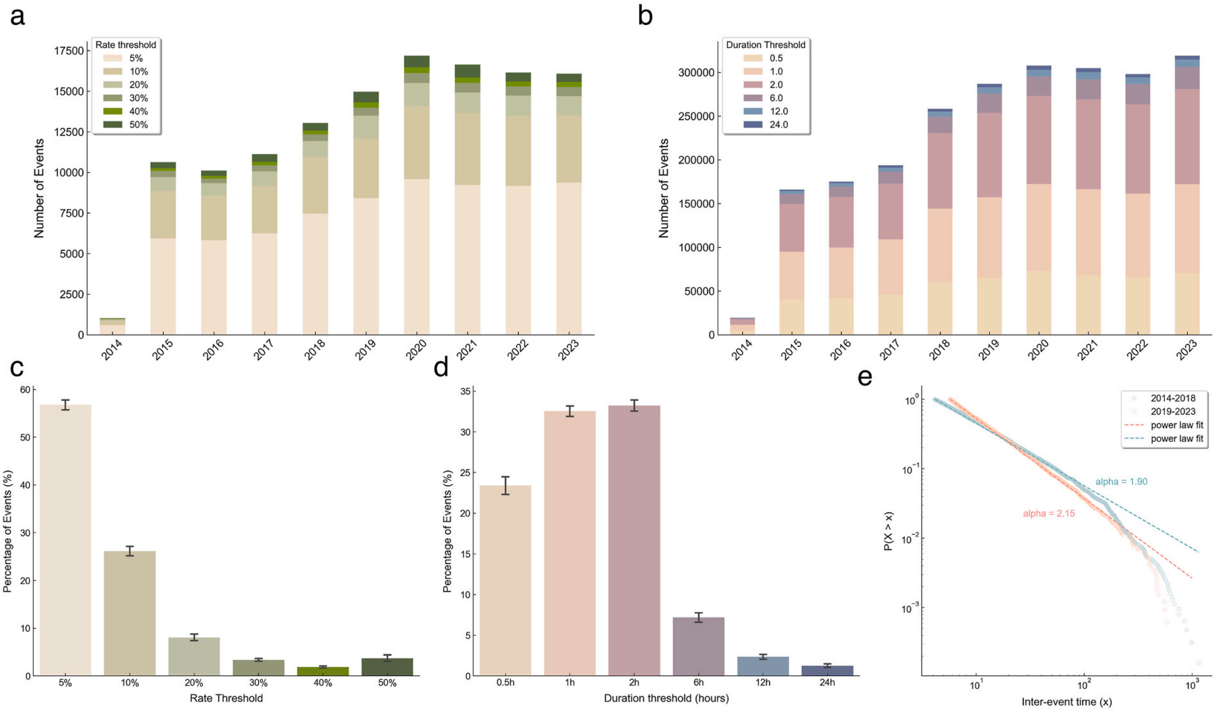

Fig. 5. Descriptive analysis of power outage frequency. a. Stacked bar plot for event numbers with varying outage intensity. b. Stacked bar plot for event numbers with varying outage duration. c. Relative proportion for all event intensity categories. d. Relative proportion for all event duration categories. The error bar denotes a 95 % confidence interval. e. Cumulative probability distribution of inter-event time for periods 2014–2018 and 2019–2023.

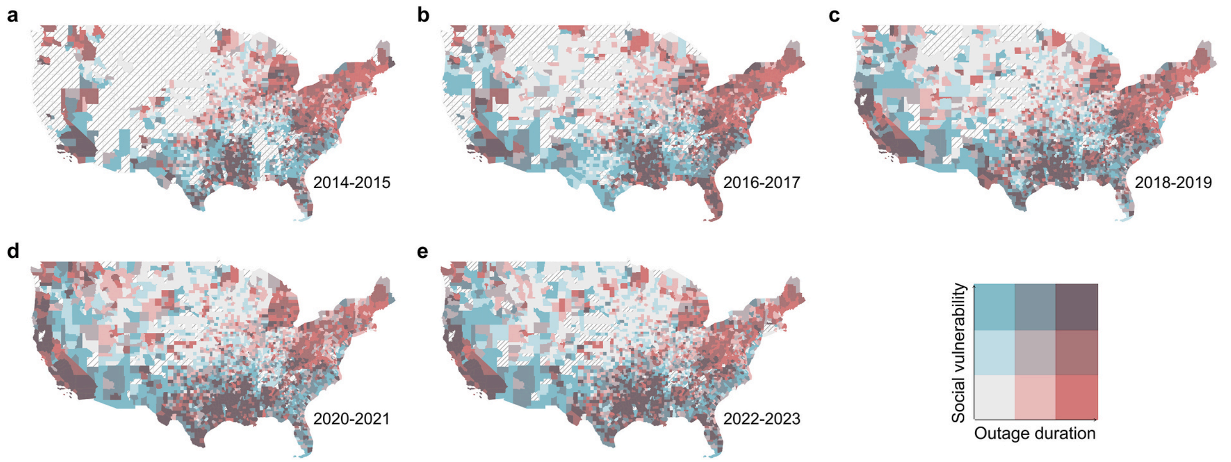

Fig. 6. Geographical distribution of counties with dual burdens from 2014 through 2023. SVI is updated every two years, so we calculated a two-year average for outage metrics to create the bivariate maps. The X-axis of the legend displays short, medium and long outage duration groups from left to right; the y-axis displays low, medium, and high social vulnerability groups from bottom to top. The upper-right grid of the legend highlights counties with dual burdens.

impact. The cumulative customer outage time reaches 7,863,993,105 customer-hours, with a mean of 2,548,280 user-hours at the county level (IQR: 169,535, 2,030,562; median: 636,909), highlighting a significant disruption to customer service, which could cause significant impact on daily life and economic activities in each county.

We observed distinct spatial patterns for the power outage metrics (Fig. 2). U.S. coastal areas, including the West Coast, East Coast, and Gulf of Mexico suffered more severely from power outages, with greater power outage frequency and longer duration. California, Washington, Maine, New Hampshire, Massachusetts, New Jersey, and Florida, experienced power outages with an interval of less than two days, while the interval for most counties in Minnesota, Iowa, and North Dakota is greater than eight days (Fig. 2d). Along with the

Table 1
Summary statistics of the six power outage metrics.

Metrics	Mean	Max	Min	Median	Interquartile range (Q1, Q3)	Standard Deviation
Number of events	999.41	5761.00	1.00	888.00	(486.25, 1369.00)	711.83
Average outage rate (%)	1.51	100.00	0.10	1.02	(0.70, 1.54)	0.03
Total duration (days)	118.79	890.25	0.01	94.69	(53.61, 155.90)	99.23
Average Inter-event time (days)	7.16	273.51	0.00	3.37	(2.22, 5.71)	16.46
Number of customers affected	540914.72	32050993	2	191556.50	(61961.75, 486026.25)	1318285.38
Cumulative customer outage time (hours)	2548280.33	137422361.5	0	636908.75	(169534.75, 2030561.69)	7027485.95

factor of denser population, coastal areas have a much higher number of affected customers and longer customer outage time. However, the average power outage rate for non-coastal states is higher than the coastal areas, indicating a higher proportion of people living in non-coastal states suffered from power system disruptions compared with those residing in coastal states.

We also identified temporal trends of power outages over the ten years (Fig. 2). For example, the yearly number of outage events has kept increasing since 2015 (Note that we only retrieved outage data of 2014 for two months, so we didn't take the year 2014 into consideration when comparing most metrics to avoid potential bias). The number of outage events surged after 2017, with a rate of approximately 30 %. From 2018 to 2023, the yearly number of outage events continued to grow at a relatively slower but steady rate. Total duration, average inter-event time, and the number of affected customers show a similar increasing trend, with a surge after 2016 (2019 for average inter-event time) and remained high during the following years. The average outage rate and cumulative outage time does not show a clear temporal pattern, which needs further analytics to identify. Overall, U.S. residents experienced more frequent power outages and endured longer outage duration over the past decade, indicating the increasing vulnerability of the power system.

3.2. Characterizing U.S. power outages regarding duration, frequency and intensity

To get a more nuanced understanding of power outage characteristics, we examined the spatial and temporal trends for each metric in detail. For power outage duration, we calculated the yearly total outage duration of each county and then normalized the indicator by dividing the length of the year. The normalized indicator is called outage duration proportion, measuring the percentage of time in a year that people experience power outages. Fig. 3a displays distributions of yearly outage duration proportion. Comparing on a year-to-year basis, the peaks of the probability density plots keep moving right, suggesting a stable increasing trend of power outage duration. In the year 2014, the probability that the duration proportion exceeds 5 % is 0.069 (95 % CI: [0.060, 0.078]), while the probability grew to 33.3 % (95 % CI: [0.315, 0.349]) in 2023. The sharp increase indicates that compared to ten years ago, U.S. residents now are more likely to experience 5 % of a year's time without power. The occurrence of outage proportion exceeding 10 %, namely more than 36.5 days without power cumulatively in a year, was scarce in 2014, with the probability of only 2 % (95 % CI: [0.015, 0.026]), while the probability has risen to 8.3 % (95 % CI: [0.074, 0.094]. The higher probability of experiencing extended power outages suggests that the reliability of the U.S. power system has deteriorated. Table SI 12 in the supplementary information shows the outage proportion threshold and corresponding probabilities for every year. From the table, we can observe the year-to-year variability of total outage duration. We also noted a surge in the extended outage probability around the year 2019, so we divided the data into two periods: before and after 2019. Fig. 3b compares the distribution plot of outage duration proportion for the two groups. Total outage duration in 2019–2023 is significantly higher than that in 2014–2018 ($p < 0.05$). The cumulative probability distribution function suggests a similar trend. The curve for 2014–2018 is consistently steeper than the curve of the latter period, illustrating that for most counties, outage duration is relatively short in this period. The flatter curve for 2019–2023 shows that counties are more likely to experience prolonged outages in the past five years. Comparing the two groups, we can find that power outages have consumed a larger fraction of the time during the most recent five years, reflecting a clear decline in power system reliability from 2014–2018 to 2019–2023. We calculated the 5-year average of outage proportion for each county and labeled them into four categories: severe (duration proportion larger than 10 %), major (duration proportion between 5 % and 10 %), moderate (duration proportion between 1 % and 5 %) and minor (duration proportion smaller than 1 %). Fig. 3c dissects the relative share of counties in each category and makes comparisons between years 2014–2018 and years 2019–2023. The results show that the number of counties falling in severe, major, and moderate categories are rising in the most recent five years. For example, 26 % of the counties (414 of 1756 counties) in the moderate category elevated into the major category, and 27 % of counties (101 of 370 counties) with major labels moved to the severe category. For counties from minor to moderate category, the percentage reaches 60 % (373 of 620 counties). In general, power outage duration for counties tend to increase to various extents in the most recent five years. As a comparison, there are fewer counties with shortening power outage duration. Furthermore, we made investigations on the counties that repetitively experienced long power outages over the years. We set four thresholds on outage duration proportion (Fig. 3d and e), and then defined hotspots as counties where the yearly accumulative outage duration exceeds these thresholds every year during the research period. For example, Kanawha County in West Virginia is the only county with ">15 %" label during 2014–2018, which means Kanawha County was without power cumulatively for more than 54 days each year. In this way, we identified areas that consistently experienced prolonged outages over the years. During 2014–2018, those hotspots are mainly found in several geographical regions, such as the northeastern areas, as well as parts of Florida, Louisiana, Texas, and California. During 2019–2023, however, the geographical range of hotspots expanded significantly, covering nearly the entire continental U.S. except for the central states. The spread of hotspots across almost the U.S.

suggests that the increasing vulnerability of power systems is becoming more pervasive and widespread. The repetitively affected areas are no longer confined to a few regions but are spreading to new areas. Numerically, the number of hotspots, across all thresholds, has increased multiple times, which means more areas consistently experiencing extended disruptions in the electricity supply.

We examined power outage intensity based on the power outage rate and the number of affected customers. To track the trend of power outage magnitude over the years, we calculated county-level average outage rate across all outage events that occurred during periods 2014–2018 and 2019–2023 separately. To facilitate comparison, we sorted the counties in descending order of average outage rate for each period and compared the outage rate values for counties in the same position. Results (Fig. 4a) show that the average outage rate during 2019–2023 is significantly higher than that during 2014–2018 (paired Wilcoxon test, $p < 0.05$), demonstrating that power outages have intensified in the past five years. Another indicator we considered is the number of customers affected by outage events, as this measure directly reflects the broad impact that power outages can have on communities. Fig. 4b captures the temporal trend of the peak number of affected customers over ten years. The peak refers to the maximum number of customers impacted across all outage events each year. We calculated this metric at the county-level and then computed the yearly average value for the entire continental United States. Despite some fluctuations, the overall trend for average peak number of customers is ascending (upper plot of Fig. 4b). Considering that the total number of covered customers keeps almost constant over the years (year-to-year percent change between −2.8 % and +3.9 %), we computed the relative proportion for peak number of affected customers and identified an even more notable increase as well (lower plot of Fig. 4b). The upward trend in both the absolute number and the relative share across the study period highlights a substantial growth in the scale and intensity of these outage events. Fig. 4c depicts the spatiotemporal trend of power outage intensity at the state level. Florida, New Jersey, Connecticut, and Washington D.C. have significant spikes, indicating that those regions have been impacted by large-scale blackouts in certain years. The lower plot of Fig. 4c displays the hotspots of the yearly accumulated number of affected customers, which is the sum of affected customers in a year. Spatially, California, Florida, and Texas have the largest number of affected customers. Temporally, we can also identify the year-to-year viability of outage intensity and the years with the most severe impacts. Those plots enable a better comparison of outage impacts across different regions and time periods.

In analyzing power outage frequency, we categorized power outage events with varying intensity and duration categories and counted the number of outage events in each category. Fig. 5a displays the trend of event numbers for all intensity categories over the ten-year study period. Overall, the event numbers are increasing with notable spikes after year 2018. A similar trend can be observed from Fig. 5b, which denotes the trend related to the event numbers for events with various duration. We examined the relative proportion of all event categories (Fig. 5c and d). Over 80 % of the outage events have a power outage rate lower than 10 %, indicating that less severe power outages are more common. However, events with an outage rate over 50 % account for approximately 4 %, suggesting that the risk of extensive outage is still a notable concern. Events with a duration of 1 to 2 hours are the most frequent, accounting for 60 %, and events lasting longer than 2 hours are much less. Interestingly, we found that the relative proportion of all event categories remained steady over the ten years. For example, events with a duration between 0.5 and 1 hour account for 23.2 % of outages with a small standard deviation of less than 1 %. Table SI 3 and SI 4 in the supplementary information shows the average proportion and standard deviation for all event categories. This finding reveals that the growth for outage events with varying intensity and duration is proportional.

Another metric we applied to measure power outage frequency is inter-event time. We examined the distribution of inter-event time for periods 2014–2018 and 2019–2023, separately. The Kolmogorov-Smirnov (K-S) test statistic is 0.02 for the period 2014–2018 and 0.01 for the period 2019–2023, meaning that both groups exhibit good power law fit. We also employed loglikelihood ratio to exclude other distributions. Prior studies suggest that outage interval follows exponential distribution [42,43]. However, compared to exponential distribution, the log-likelihood ratio for period 2014–2018 is 2814.2 with $p < 0.05$, and 1344.2 with $p < 0.05$ for the period 2019–2023, suggesting power law is a better fit. As power law distribution usually emerges from complex systems with interconnected components and cascading failures, the fitted distribution suggests that power systems are complex networks in which local failure can trigger cascading effects, leading to large-scale disruptions. Power law fit for outage inter-event time indicates that the occurrence of outages is not random, but rather follows a specific statistical pattern. In this way, the fitted power law distribution can assist with the outage occurrence prediction. Fig. 5e displays the fitted parameters of power law distributions. Distributions for the two groups are statistically different (K-S test, $p < 0.05$). The fitted parameter alpha for both groups suggests a heavier tail for the period 2014–2018, indicating that longer intervals between outage events are more likely during that time. In other words, the intervals between outage events tend to become shorter, resulting in more frequent occurrence of power disruptions in the most recent five years.

3.3. *Capturing unequal power outage distribution regarding socioeconomic status and geographical regions*

We used the social vulnerability index published by US Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry (CDC/ATSDR) as a comprehensive indicator for socioeconomic status and then examined the relationship between power outage metrics and SVI. We categorized counties into three groups based on the tertiles of SVI, and labeled groups as low, medium, and high social vulnerability. Similarly, we categorized and labeled counties with tertiles of every power outage metric: the number of events, outage rate, outage duration, and inter-event time. Fig. 6 shows the geographical distribution of areas with varying extent of social and power system vulnerability for outage duration. Figures for the other outage metrics are available in supplementary information (Fig. SI 2-4). We defined counties with high social vulnerability and severe power outages as counties with dual burdens since those counties are vulnerable to both social and power system challenges that can exacerbate their difficulties during crises. From the figures, we can observe that the geographical range of counties with dual burdens is largely expanding, especially in

California, Texas, Louisiana, and Florida.

Further, we performed an ordinary least square (OLS) regression to further assess the relationship between SVI and power outage metrics. Results show significant positive associations between SVI and all the outage metrics (Fig. 7), illustrating that population groups with higher social vulnerability tend to suffer from outages with higher frequency, longer duration, and larger scale. The association suggests that systematic inequality may exacerbate the adverse effects of power outages on socially disadvantaged groups, causing significant hardship and negative well-being effects and even potentially leading to a cycle of vulnerability. Moreover, OLS regression was performed every two years from 2014 through 2023, and the coefficients keep an increasing trend over the years. This trend suggests that the disparity in outage metrics across populations with varying degrees of vulnerability has been widening over the past decade. The growing disparity is noteworthy, as this reflects that infrastructure maintenance and upgrade policies may not adequately address equity in infrastructure prioritization and resource allocation over the years.

The analysis results related to the counties with dual burdens demonstrate a similar temporal trend. Fig. 8 shows that counties with dual burdens have experienced more severe outages over the years, characterized by a greater number of power disruptions, prolonged time without power, larger scale, and shorter outage intervals. This observation indicates a compounding effect where both social and power system vulnerability interact with each other, leading to disproportionately severe impacts on the residents in these counties. Power system failure may amplify the negative effects of issues, such as housing instability, unemployment, limited access to resources [45], and raising more health and safety concerns. The worsening trend highlights the urgent need for targeted policies and programs to enhance the robustness and resilience of the power system.

We also examined the relationship between power outage metrics and urbanicity. Counties were grouped into either urban or rural

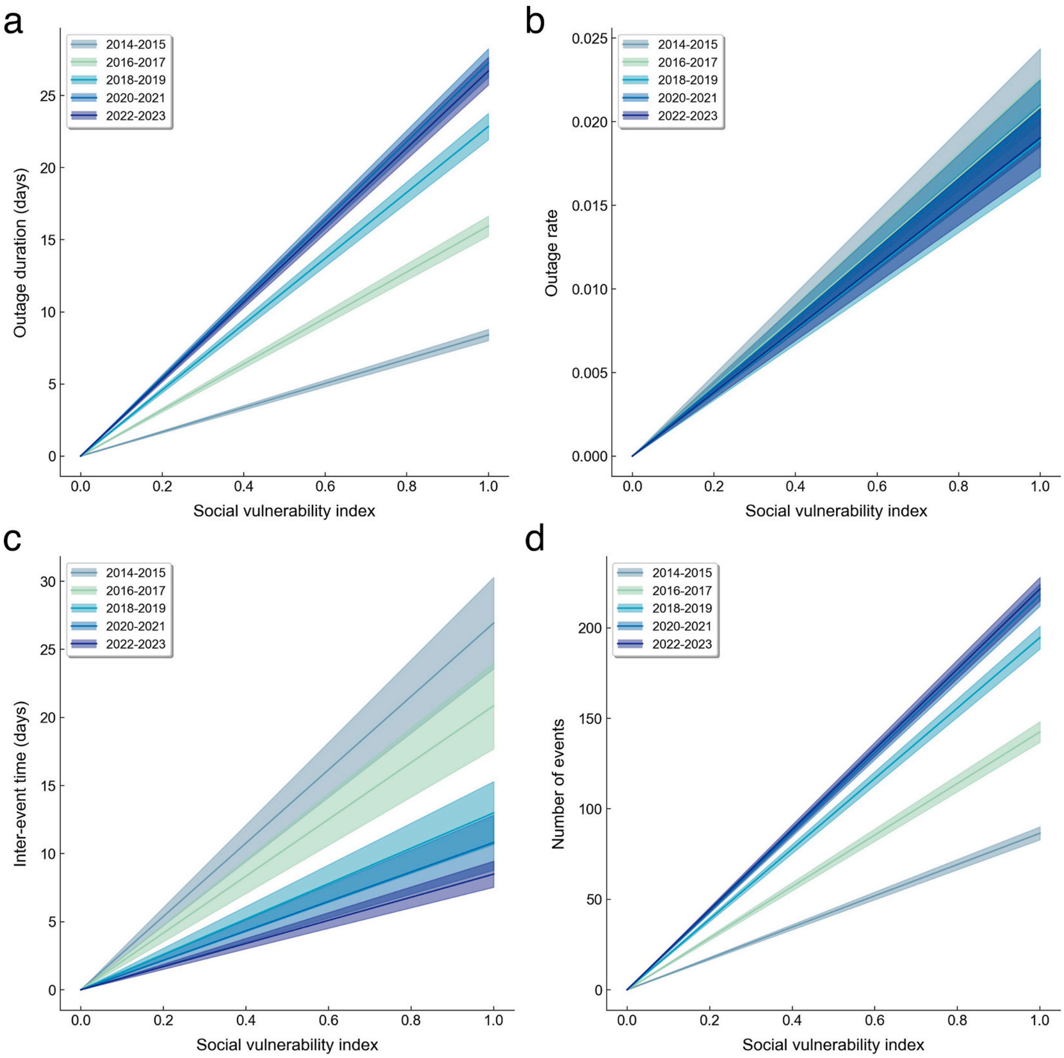

Fig. 7. OLS regression between SVI and outage metrics. a. OLS regression between SVI and outage duration. b. OLS regression between SVI and outage rate. c. OLS regression between SVI and inter-event time. d. OLS regression between SVI and number of events. The shaded area denotes a 95 % confidence interval of the plot.

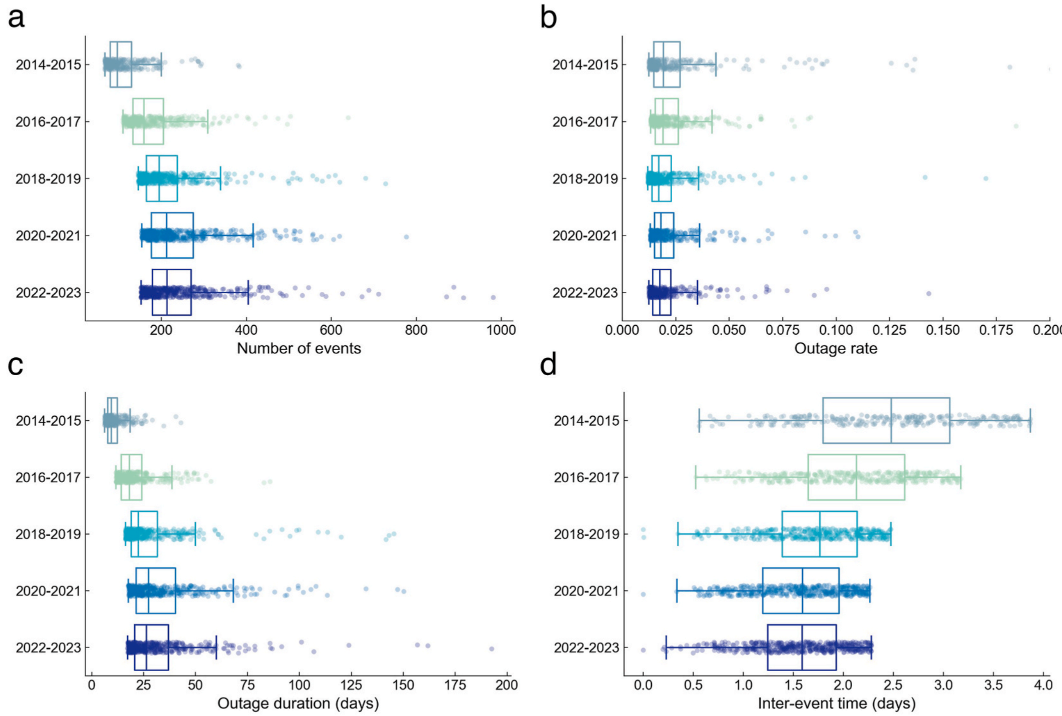

Fig. 8. Distribution plots of outage metrics over the past ten years for counties with dual burdens. a. Boxplot for number of events. b. Boxplot for outage rate. c. Boxplot for outage duration. d. Boxplot for inter-event time. The Kruskal-Wallis H test was employed to determine the significance of differences among the five groups ($p < 0.05$).

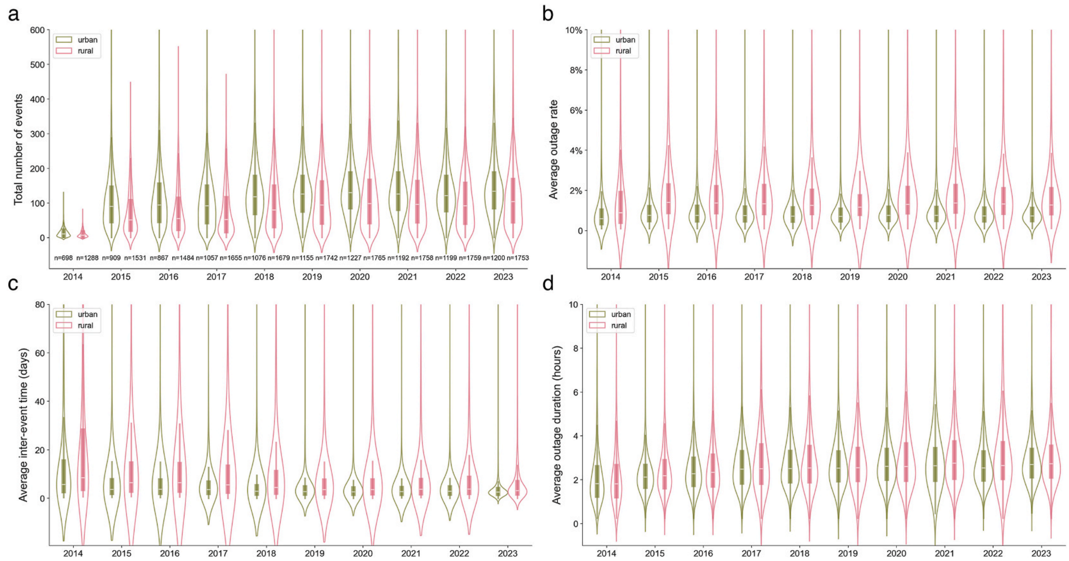

Fig. 9. Urban-rural differences regarding power outage metrics. a. Total number of events is higher in urban regions compared to rural regions. Numbers at the bottom of the plot denote county numbers for each group. The numbers are the same for Fig. 9b, c and 9d b. The average outage rate is lower in urban regions. **c.** The average inter-event time is shorter in urban regions. d. The average outage duration is longer in rural regions. The Mann-Whitney U test was performed to examine group differences ($p < 0.05$ for all groups except for average outage duration of year 2014, 2016–2020 and year 2023).

categories and compared between the two categories. Notably, urban and rural areas exhibit opposite patterns in the characteristics of power outages. Urban areas experience a higher number of outage events and shorter intervals between events each year during the study period, while the average outage rate is lower than that of rural regions (Fig. 9a–c, Man-Whitney U test, $p < 0.05$ for all groups).

The differences in the outage duration are significant for years 2015, 2021, and 2022 during which urban areas show slightly shorter average outage duration (Fig. 9d, Man-Whitney U test, $p < 0.05$). From these analysis, urban outage events can be characterized as high-frequency, short-term, and small-scale disruptions. In contrast, rural power outages are less frequent but tend to last longer and affect a larger proportion of customers once they occur. These contrasting outage patterns highlight unique operational challenges faced by rural and urban regions. In urban areas, the higher frequency of outages can be attributed to the dense development and co-location of electric infrastructure with other built-environment elements that elevate the likelihood of cascading incidents, such as equipment failures, accidents, and construction activities. Rural regions face prolonged outage, primarily due to geographical and logistical constraints inherent in their system design and service environment. Prior studies emphasize that the sparse and radial configuration of rural distribution systems, together with the wide geographic dispersion and limited accessibility of infrastructure, constrains network redundancy and hinders the rapid mobilization of restoration crews and resources [46,47]. Moreover, utilities serving low-density service territories are often deprioritized in restoration sequencing, since restoration decisions tend to maximize the number of customers restored per unit effort [48]. Addressing these challenges requires strategies that improve restoration readiness and decentralized power supply capability. Research highlights the importance of pre-positioning repair resources, reinforcing critical feeders to enhance redundancy, and deploying distributed or microgrid-based supplies to sustain essential loads during prolonged disruptions [49,50].

4. Discussion

Although there is considerable anecdotal evidence highlighting the vulnerabilities of the U.S. power infrastructure, comprehensive studies that systematically analyze these issues over time and across the nation are scarce. A data-driven, nationwide analysis that characterizes the spatial and temporal trends in power outage characteristics is essential for understanding both day-to-day reliability issues and system responses to extreme events. Such an analysis is essential for accurately assessing the severity of the problem, understanding the spatiotemporal characteristics, and informing the development of effective policies and programs aimed at enhancing the resilience and reliability of the U.S. power systems. This approach would provide the necessary foundation for strategic planning and investment to protect against future disruptions. Recognizing this need, we retrieved 179,053,397 county-level power outage records with a 15-minute interval across 3,022 U. S. counties during 2014–2023 to capture power outage characteristics. We applied a vulnerability assessment model to examine power outages from intensity, frequency and duration dimensions. We developed multiple metrics for each dimension as measurements and then utilized the metrics to characterize the spatial and temporal trends. These metrics collectively depict how the U.S. power infrastructure performs under both routine operational stress and extreme conditions. On average, U.S. counties experienced nearly 1,000 power outage events over the ten-year study period and were without power for an average total of 118.79 days, which corresponds to an average of 3.65 % of the total time across the decade. Power outage events occurred approximately every 7 days, indicating that counties were without power once a week. The average outage rate is around 1 %; if multiplied by the larger number of power system customers, this seemingly small percentage translates into a substantial number of affected customers. The accumulative outage customer-time reached 7.8 billion customer-hours, indicating the vast scale of impacts on social activities and well-being. These results depict a sketchy but alarming picture of how ubiquitous and widespread power outages have been across the country.

We performed further analyses on the power outage metrics across the three dimensions to reveal important spatial and temporal patterns. Outage metrics consistently show an increasing trend of U.S. power systems vulnerability over the past decade. Power outages in the U.S. are becoming prolonged, intensified, and more frequent. Comparatively, residents on average spent 2 % of the time without power during 2014–2018, while the percentage rose to 8.3 % during 2019–2023. The impact scale of outages can be inferred from both the growing average outage rate and the number of customers affected. For example, outages at their peak moment in 2015 on average left 15 % of the customers without power, while peak moments of outages in 2020 increased to 30 %. The number of outage events maintained an upward trend for every intensity and duration category. Following power law distribution, the event interval for 2019–2023 has a lighter tail compared with that of 2014–2018, meaning that shorter intervals between outages have become more likely over the past five years. The worsening trend for all power outage metrics underscores that U.S. power systems are faced with increasing vulnerability. Based on the data-driven national-level evaluations of the duration, frequency, and intensity of power outages, infrastructure owners, operators, and policymakers can better understand the urgency of taking action to improve the resilience and reliability of power infrastructure in the U.S.

The characteristics of power outages display certain spatial patterns. For example, areas repetitively affected by prolonged power outages are primarily located in coastal regions. The coastal states of California, Texas, and Florida are on the top list regarding the number of customers being affected by outage events. The spatial patterns also indicate the existence of potential disparities. We also observed distinct power outage characteristics between urban and rural regions. Power outages in urban regions are more frequent with lower intensity and shorter duration, while rural outages are less common but yield to larger impact scale. Spatial variabilities also exist among different power grid connectivity regions. Compared to the East Interconnections, the West Interconnections and Texas have accounted for a relatively larger share of outage duration in recent years, reflecting the greater challenges these regions face in maintaining grid stability (See Supplementary Information).

Previous literature has noted that power outages disproportionately affect socioeconomically disadvantaged population groups such as low-income and minority groups [8,51,52], most in weather-related power outage events. This study incorporated the social vulnerability index into ten-year national power outage data and identified positive association between SVI and outage metrics. This finding indicates that the disparity is not confined to certain areas or events. Instead, it might be a systematic issue that socially vulnerable groups are continuously faced with more frequent, larger scale and prolonged power outages. More notably, the positive association is becoming stronger over the years, indicating an enlarging gap of outage disparities. Areas with high social vulnerability have been experiencing worsening power outage issues, such as longer time without power and shorter intervals between outage events. This increasing disparity highlights a concerning trend that power system resilience and reliability of socially vulnerable communities are further compromised. Building on these findings, it is important to consider how resilience and reliability interventions can be prioritized across different outage–vulnerability combinations. The "dual-burden" framework suggests that areas with both high outage exposure and high social vulnerability should be prioritized, as these communities face compound risks of a higher likelihood of service disruption and lower capacity to withstand and recover from those disruptions. These areas should therefore be prioritized for integrated interventions enhancing both infrastructures and community adaptive capacity. However, prioritization strategies may differ when the two dimensions do not align. Regions with high outage exposure but lower social vulnerability may benefit most from technical and infrastructural measures, such as grid modernization, redundancy, vegetation management, and other hardening strategies [53,54], to enhance overall grid performance and reduce the occurrence, scale, and duration of power outages. Conversely, areas with high social vulnerability but lower outage exposure may require social and institutional interventions, including resilience hubs, access to backup power for critical services, and enhanced emergency communication systems, to mitigate the severe impacts that outages can have on socially vulnerable populations. Recognizing these nuanced trade-offs can guide policymakers and utilities in designing targeted strategies that balance improvements in infrastructure performance with considerations of social equity.

The findings of this study offer important contributions. The results provide empirical evidence revealing the extent, spatial variation, and temporal escalation of power system vulnerability across the United States. Unlike most event-specific studies that focus on individual disasters, this research offers a longitudinal and national-level perspective on the magnitude, hotspots, and evolution of community exposure to power outages. The developed metrics collectively depict how the U.S. power infrastructure performs under both routine operational stresses and extreme conditions, offering a holistic view of system performance across diverse operating conditions. This inclusive approach is important because the mechanisms underlying day-to-day service interruptions and large-scale disruptions are not independent, but rather part of the same continuum of system performance. Understanding this continuum requires recognizing two closely related but distinct dimensions: reliability and resilience. Reliability describes the system's ability to maintain service under normal conditions, while resilience reflects its capacity to withstand, adapt to, and recover from rare, high-impact events (Panteli et al., 2017). Inherently, reliability and resilience are interdependent. Reliability performance under routine conditions influences resilience outcomes during major disruptions. Frequent, lower-impact outages can reveal chronic stressors and structural weaknesses, such as asset aging, vegetation interference, or weather sensitivity [55,56], that also shape the system's response under extreme conditions [57]. Therefore, recent studies increasingly emphasize the need to integrate resilience considerations alongside traditional reliability assessment in power system planning and evaluation [58,59]. By incorporating all outage records, this study provides a comprehensive assessment of U.S. power system robustness, capturing both chronic operational vulnerabilities and acute hazard-driven disruptions. These insights advance a holistic understanding of power system vulnerability, offer an evidence base that can inform and support utilities, policymakers, and community leaders in refining investment strategies and prioritizing actions aimed at enhancing the resilience and reliability of the nation's power infrastructure.

There are also limitations of this study. First, the country-level assessment may obscure finer-scale variations, particularly in areas experiencing rapid development and population growth. While our analysis revealed a positive correlation between county-level outage metrics and social vulnerability as measured by the SVI, this relationship may differ when examined at sub-county or household scales. Although the SVI is a standardized and nationally consistent measure for social disadvantages, it is constrained by its fixed set of variables and general multi-hazard design, which may not fully capture populations uniquely vulnerable to power outages. Future research could build on this work by integrating higher-resolution datasets, such as the ResStock built by the National Renewable Energy Laboratory, which provides detailed information on building stock energy consumption, end-use profiles, and building characteristics [60]. Coupling such micro-level data with outage observations at finer spatial resolutions could better capture energy dependence, adaptive capacity, and outage sensitivity among different population groups. This integration would enable a more granular understanding of how social and infrastructural vulnerabilities intersect with each other. Second, our assessment does not account for the intricate economic and physical interdependencies across geographic regions. The power system is a complex network with interdependent relationships between transmission and distribution grids of various sizes. Although our study's original data is at the county level and considers grid connectivity as a distinguishing factor from geographic structure, future studies should incorporate more data on the transmission and distribution of power grids across regions to effectively differentiate spatial differences in power outage vulnerability. Third, we acknowledged that data coverage varied slighted over the study period, with fluctuations of less than ± 3 %. Those minor variations are not likely to influence the observed escalating power outage tendency. Nevertheless, minor bias from uneven reporting may remain, and we have explicitly noted this limitation to maintain transparency in interpretation.

CRediT authorship contribution statement

Bo Li: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Junwei Ma:** Writing – review & editing, Writing – original draft, Visualization, Methodology. **Olufemi A. Omitaomu:** Writing – review & editing, Data curation. **Ali Mostafavi:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Science Foundation under Grant CMMI-1846069 (CAREER). Any opinions, findings, conclusions, or recommendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agencies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2025.105980.

Data availability

Data will be made available on request.

References

[1] Federal Energy Regulatory Commission, N.A.E.R.C., Regional Entities, FERC-NERC-Regional Entigy Staff Report: the February 2021Cold Weather Outages in Texas and the South Central United States, 2021.
[2] NOAA, Ian is the 15th billion-dollar disaster this year so far, Available from: https://www.noaa.gov/news/ian-is-15th-billion-dollar-disaster-year-so-far, 2022.
[3] U.S. Department of Energy, Hurricane Ian Situation Report #13, 2022.
[4] W.D. Cara Kuuskvere, The aging US power grid: navigating toward modernization, Available from: https://sepapower.org/knowledge/the-aging-us-power-grid-navigating-toward-modernization/, 2024.
[5] Jeff Postelwait, Future shock: how aging infrastructure, rising demand, and tight budgets continue to shape the T&D industry, Available from: https://www.tdworld.com/utility-business/article/55142931/future-shock-how-aging-infrastructure-rising-demand-and-tight-budgets-continue-to-shape-the-td-industry, 2024.
[6] U. Shahzad, The concept of vulnerability and resilience in electric power systems, Aust. J. Electr. Electron. Eng. 18 (3) (2021) 138–145.
[7] G.L. Tonn, et al., Hurricane isaac: a longitudinal analysis of storm characteristics and power outage risk, Risk Anal. 36 (10) (2016) 1936–1947.
[8] C.-C. Lee, M. Maron, A. Mostafavi, Community-scale big data reveals disparate impacts of the Texas winter storm of 2021 and its managed power outage, Humanit. Soc. Sci. Commun. 9 (1) (2022) 1–12.
[9] N.M. Flores, et al., The 2021 Texas power crisis: distribution, duration, and disparities, J. Expo. Sci. Environ. Epidemiol. 33 (1) (2023) 21–31.
[10] N.M. Flores, et al., Powerless in the storm: severe weather-driven power outages in New York state, 2017–2020, PLOS Climate 3 (5) (2024) e0000364.
[11] N. Masoudvaziri, et al., Integrated risk-informed decision framework to minimize wildfire-induced power outage risks: a county-level spatiotemporal analysis, in: Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference, Venice Italy, 2020.
[12] C. Ji, et al., Large-scale data analysis of power grid resilience across multiple US service regions, Nat. Energy 1 (5) (2016) 1–8.
[13] V. Do, et al., Spatiotemporal distribution of power outages with climate events and social vulnerability in the USA, Nat. Commun. 14 (1) (2023) 2470.
[14] A. Ankit, et al., US resilience to large-scale power outages in 2002–2019, Journal of safety science and resilience 3 (2) (2022) 128–135.
[15] L.N. Dunn, et al., Exploratory analysis of high-resolution power interruption data reveals spatial and temporal heterogeneity in electric grid reliability, Energy Policy 129 (2019) 206–214.
[16] IEEE std 1366-2022, IEEE Guide for Electric Power Distribution Reliability Indices.
[17] N. Singh, O.A. Omitaomu, Spatiotemporal variability of electric system reliability metrics, in: Proceedings of the 1st ACM SIGSPATIAL International Workshop on Advances in Urban-AI, 2023.
[18] M. Abdelmalak, et al., Quantitative resilience-based assessment framework using eagle-i power outage data, IEEE Access 11 (2023) 7682–7697.
[19] K. Zhou, et al., Bayesian estimates of transmission line outage rates that consider line dependencies, IEEE Trans. Power Syst. 36 (2) (2020) 1095–1106.
[20] J.A. Casey, et al., Measuring long-term exposure to wildfire PM2. 5 in California: time-varying inequities in environmental burden, Proc. Natl. Acad. Sci. 121 (8) (2024) e2306729121.
[21] L. Miao, et al., Unveiling the dynamics of sequential extreme precipitation-heatwave compounds in China, npj Clim. Atmos. Sci. 7 (1) (2024) 67.
[22] C. Brelsford, et al., A dataset of recorded electricity outages by United States county 2014–2022, Sci. Data 11 (1) (2024) 271.
[23] U.S.D.o. Energy, Environment for analysis of geo-located energy information. https://eagle-i.doe.gov/login.
[24] U.S.Department of energy [cited 2024 03-06]; Available from: https://eagle-i.doe.gov/login.
[25] C. Dominianni, et al., Power outage preparedness and concern among vulnerable New York city residents, J. Urban Health 95 (2018) 716–726.
[26] D. Carr, M. Thomson, Non-technical electricity losses, Energies 15 (6) (2022) 2218.
[27] M.J. Nieuwenhuijsen, Exposure Assessment in Environmental Epidemiology, Oxford University Press, USA, 2015.
[28] J. Ma, A. Mostafavi, Urban form and structure explain variability in spatial inequality of property flood risk among US counties, Commun. Earth Environ. 5 (1) (2024) 172.
[29] D. Molitor, J.T. Mullins, C. White, Air pollution and suicide in rural and urban America: evidence from wildfire smoke, Proc. Natl. Acad. Sci. 120 (38) (2023) e2221621120.
[30] National Center for Health Statistics, NCHS urban-rural classification scheme for counties, Available from: https://www.cdc.gov/nchs/data_access/urban_rural.htm#Data_Files_and_Documentation, 2013.
[31] S.C. Ganz, C. Duan, C. Ji, Socioeconomic vulnerability and differential impact of severe weather-induced power outages, PNAS Nexus 2 (10) (2023) pgad295.
[32] A. Bhattacharyya, M. Hastak, A data-driven approach to quantify disparities in power outages, Sci. Rep. 13 (1) (2023) 7247.
[33] B.E. Flanagan, et al., A social vulnerability index for disaster management, J. Homel. Secur. Emerg. Manag. 8 (1) (2011) 0000102202154773551792.
[34] S. Guikema, et al., Climate change impacts on tropical cyclone–induced power outage risk: sociodemographic differences in outage burdens, Proc. Natl. Acad. Sci. 122 (43) (2025) e2502266122.
[35] A. Nejat, et al., Equitable community resilience: the case of winter storm Uri in Texas, Int. J. Disaster Risk Reduct. 77 (2022) 103070.

[36] F. Tormos-Aponte, G. García-López, M.A. Painter, Energy inequality and clientelism in the wake of disasters: from colorblind to affirmative power restoration, Energy Policy 158 (2021) 112550.
[37] F. Ezzati, et al., Power outage-risk integrated social vulnerability analysis highlights disparities in small residential communities, Commun. Earth Environ. 6 (1) (2025) 294.
[38] J.P. Montoya-Rincon, et al., A socio-technical approach for the assessment of critical infrastructure system vulnerability in extreme weather events, Nat. Energy 8 (9) (2023) 1002–1012.
[39] United States Environmental Protection Agency. U.S. grid regions. [cited 2024 05-18]; Available from: https://www.epa.gov/green-power-markets/us-grid-regions.
[40] North American electric reliability corporation [cited 2024 05-02]; Available from: https://www.nerc.com/Pages/default.aspx.
[41] A. Clauset, C.R. Shalizi, M.E. Newman, Power-law distributions in empirical data, SIAM Rev. 51 (4) (2009) 661–703.
[42] J. Chen, J.S. Thorp, M. Parashar, Analysis of electric power system disturbance data, in: Hicss, Citeseer, 2001.
[43] B.A. Carreras, D.E. Newman, I. Dobson, North American blackout time series statistics and implications for blackout risk, IEEE Trans. Power Syst. 31 (6) (2016) 4406–4414.
[44] U.S. Census Bureau, TIGER/line shapefile, 2019, nation, U.S., current county and equivalent national shapefile, Available from: https://catalog.data.gov/dataset/tiger-line-shapefile-2019-nation-u-s-current-county-and-equivalent-national-shapefile, 2019.
[45] J. Dargin, A. Mostafavi, Dissecting heterogeneous pathways to disparate household-level impacts due to infrastructure service disruptions, Int. J. Disaster Risk Reduct. 83 (2022) 103351.
[46] A.K. Erenoğlu, I. Sengor, O. Erdinç, Power system resiliency: a comprehensive overview from implementation aspects and innovative concepts, Energy Nexus 15 (2024) 100311.
[47] F. Rouhana, et al., Examining rural–urban vulnerability inequality in extreme weather-related power outages: case of tropical storm isaias, Nat. Hazards Rev. 26 (3) (2025) 04025039.
[48] Pacific Northwest National Laboratory, Community Energy Resilience Planning for Extended Power Outages, 2023.
[49] C. Wang, et al., A systematic review on power system resilience from the perspective of generation, network, and load, Renew. Sustain. Energy Rev. 167 (2022) 112567.
[50] D. Baghbanzadeh, et al., Resilience improvement of multi-microgrid distribution networks using distributed generation, Sustainable Energy, Grids and Networks 27 (2021) 100503.
[51] N. Coleman, et al., Energy inequality in climate hazards: empirical evidence of social and spatial disparities in managed and hazard-induced power outages, Sustain. Cities Soc. 92 (2023) 104491.
[52] R.S. Liévanos, C. Horne, Unequal resilience: the duration of electricity outages, Energy Policy 108 (2017) 201–211.
[53] T. Kemabonta, G. Mowry, A syncretistic approach to grid reliability and resilience: investigations from Minnesota, Energy Strategy Rev. 38 (2021) 100726.
[54] M. Panteli, et al., Power systems resilience assessment: hardening and smart operational enhancement strategies, Proc. IEEE 105 (7) (2017) 1202–1213.
[55] A.M.L. da Silva, L.F. Araújo, Reliability evaluation of generating systems considering aging processes, Elec. Power Syst. Res. 202 (2022) 107589.
[56] D. Cerrai, P. Watson, E.N. Anagnostou, Assessing the effects of a vegetation management standard on distribution grid outage rates, Elec. Power Syst. Res. 175 (2019) 105909.
[57] A. Ahmad, I. Dobson, Towards using utility data to quantify how investments would have increased the wind resilience of distribution systems, IEEE Trans. Power Syst. 39 (4) (2023) 5956–5968.
[58] M.H.N. Amiri, F. Guéniat, Towards a framework for measurements of power systems resiliency: comprehensive review and development of graph and vector-based resilience metrics, Sustain. Cities Soc. 109 (2024) 105517.
[59] R. Moreno, et al., From reliability to resilience: planning the grid against the extremes, IEEE Power Energy Mag. 18 (4) (2020) 41–53.
[60] National Renewable Energy Laboratory, Resstock: Highly Granular Modeling of the U.S. Housing Stock.