ARTICLE

The 2021 Texas Power Crisis: distribution, duration, and disparities

Nina M. Flores [1✉], Heather McBrien[1], Vivian Do[1], Mathew V. Kiang[2], Jeffrey Schlegelmilch[3] and Joan A. Casey[1]

BACKGROUND: Precipitated by an unusual winter storm, the 2021 Texas Power Crisis lasted February 10 to 27 leaving millions of customers without power. Such large-scale outages can have severe health consequences, especially among vulnerable subpopulations such as those reliant on electricity to power medical equipment, but limited studies have evaluated sociodemographic disparities associated with outages.
OBJECTIVE: To characterize the 2021 Texas Power Crisis in relation to distribution, duration, preparedness, and issues of environmental justice.
METHODS: We used hourly Texas-wide county-level power outage data to estimate geographic clustering and association between outage exposure (distribution and duration) and six measures of racial, social, political, and/or medical vulnerability: Black and Hispanic populations, the Centers for Disease Control and Prevention (CDC) Social Vulnerability Index (SVI), Medicare electricity-dependent durable medical equipment (DME) usage, nursing homes, and hospitals. To examine individual-level experience and preparedness, we used a preexisting and non-representative internet survey.
RESULTS: At the peak of the Texas Power Crisis, nearly 1/3 of customers statewide ($N = 4{,}011{,}776$ households/businesses) lost power. We identified multiple counties that faced a dual burden of racial/social/medical vulnerability and power outage exposure, after accounting for multiple comparisons. County-level spatial analyses indicated that counties where more Hispanic residents resided tended to endure more severe outages (OR = 1.16, 95% CI: 1.02, 1.40). We did not observe socioeconomic or medical disparities. With individual-level survey data among 1038 respondents, we found that Black respondents were more likely to report outages lasting 24+ hours and that younger individuals and those with lower educational attainment were less likely to be prepared for outages.
SIGNIFICANCE: Power outages can be deadly, and medically vulnerable, socioeconomically vulnerable, and marginalized groups may be disproportionately impacted or less prepared. Climate and energy policy must equitably address power outages, future grid improvements, and disaster preparedness and management.

Keywords: Power outage; Durable medical equipment; Texas; Climate change; Extreme cold weather; Environmental justice

INTRODUCTION

In February 2021, a series of winter storms brought the coldest temperatures in 70+ years to Texas, leading to over 2 weeks of sweeping power outages, termed the 2021 Texas Power Crisis [1]. Texas's Department of Health and Human Services has attributed 210 deaths to the outages, with causes like hypothermia and carbon monoxide poisoning [2], but the true number of outage-related deaths may top 700 when considering indirect deaths [3]. Three factors led to severe outages. First, electricity and gas systems were insufficiently winterized. Second, the Electric Reliability Council of Texas (ERCOT) grid, serving over 90% of Texans, is largely isolated from the national grid, which limited electricity import. And third, several thermal plants were out of service for scheduled maintenance in anticipation of milder

temperatures [1]. As climate change continues to increase the frequency of extreme weather events, including, counterintuitively, extreme cold events, it is critical to understand the regions and individuals most vulnerable to power outages [4].

Power outages do not affect all groups equally. While outages are inconvenient for everyone, they can be dangerous for certain vulnerable groups including those reliant on electricity-dependent durable medical equipment (DME), those with underlying conditions, those who need refrigerated medications, and older adults [5, 6]. A broad literature highlights how historically marginalized and disadvantaged groups face disproportionate climate-driven exposures and restricted capacity to prepare for and recover from these extreme events [7, 8]. As extreme events cause most long outages in the US, similar environmental justice (EJ) concerns may

[1]Department of Environmental Health Sciences, Columbia University Mailman School of Public Health, New York, NY, USA. [2]Department of Epidemiology and Population Health, Stanford University School of Medicine, Stanford, CA, USA. [3]National Center for Disaster Preparedness at the Columbia Climate School, Columbia University, New York, NY, USA. ✉email: nf2497@cumc.columbia.edu

extend to outage events. Evidence is sparse but some studies find that older adults, lower-income families, communities of color, and those with language barriers are more likely to experience outages, may experience longer outage durations after extreme events [9–13], and are less likely to be prepared for outages [9]. An existing report monitoring the Texas outages via nighttime satellite imagery [14] and media outlets [15] pointed to inequities during the crisis in terms of who lost power and for how long; these sources suggested that Black and Hispanic populations may have been more likely to experience the outages and may have been less able to cope with the outages by using generators or evacuating to hotels. In the current study, we investigate these findings to understand the distribution of outages across indicators of medical and socioeconomic vulnerability more fully. EJ considerations in relation to power outages fall within a broader just energy systems framework, which has the goal of reducing the socioeconomic and health burdens associated with energy systems through increased accessibility, affordability, cleanliness, and management of energy in all communities [16]. Though outside the scope of the current study, growing evidence highlights that legacies of racial discrimination such as redlining and zoning have contributed to disproportionate exposure to upstream fossil fuel production [17] as well as levels of energy inefficiency and insecurity among communities of color [18–20]—which may in turn heighten power outage experiences.

We use two datasets to assess the distribution and duration of outages during the 2021 Texas Power Crisis through an EJ lens and find county-level racial/ethnic but not socioeconomic or medical disparities in exposure to the Texas Power Crisis as well as individual-level reports of lower preparedness among lower socio-economic status (SES) and younger participants. Our inquiry into this dynamic could inform more equitable decision-making on grid improvements, disaster management, and power restoration.

MATERIALS/SUBJECTS AND METHODS
Study overview
This study consists of two analyses, both aimed at characterizing the 2021 Texas Power Crisis in relation to distribution, duration, preparedness, and issues of EJ. We draw on county-level power outage and demographic data, in addition to an existing internet survey of Texas residents, oversampled from the Permian Basin.

PowerOutage.US
We purchased data on the number of customers without power at the county level in hourly-level aggregations between February 10–24, 2021 from PowerOutage.US, which collects outage information directly from individual electric utility Application Programming Interfaces (APIs). Data elements included date and time (hourly) and county-level number of customers without power (Supplementary Methods). A customer refers to a household or a business. We estimated that the utilities the Power-Outage.US API-collected data from served 12,965,892 customers throughout Texas, amounting to over 97% of Texas customers.

ERCOT
Three main electricity grids serve the contiguous US: the Western Interconnection, the Eastern Interconnection, and the Texas Interconnection (ERCOT). ERCOT reaches 213 (84%) counties and 11,853,988 (91%) customers in Texas [21] and is separated from the rest of the country to avoid federal regulation, which may partially explain the inadequately weatherized grid [22]. We classified counties as ERCOT/non-ERCOT [21].

Outage definitions
Our primary outcome of interest was power outage experience during the 2021 Texas Power Crisis. We defined power outage at the county-level using the number (absolute) and percentage (relative) of customers out and subsequently created a measure of "severe" power outage.

To construct an absolute metric, we calculated the absolute power-out person-time between February 10–24 by summing the number of customers out at each hour by county across the period. For a secondary absolute measure, we calculated the average number of customers without power for each county during the crisis.

For our relative metric, we used a percentage that considered both the number of customers without power and the number of total customers over the entire period. To compute the relative metric for each county, we used the following equation:

$$\frac{\text{total customer} - \text{hours without power}}{(\text{total customers served})(\text{total hours reported})}(100)$$

Next, we generated binary variables indicating whether a county experienced a severe, medically-relevant outage. We considered a medically-relevant outage an outage lasting longer than 24 h that affected ≥10,000 customers (absolute scale) or ≥20% (relative scale) of customers in each county. While there is no set definition to indicate whether a region is experiencing an outage, several groups have created definitions [23–26]. For example, the Texas Public Utility Commission (PUC) defines an outage with an absolute definition of 20,000 customers out within a utility and a relative definition of 20% of total customers out within a utility (Supplementary Table 1) [24, 26]. We defined outages similarly. On the absolute scale, we defined a severe outage as a county having 10,000 customers without power for at least 24 consecutive hours during the crisis. This outcome was restricted to counties with at least 10,000 customers ($N = 115$, 45% of counties in the state). We opted to use 10,000 customers out as an absolute definition based on the distribution of the data and desire to capture experiences for denser counties, while having a sufficient sample size for analysis. On the relative scale, we defined a severe outage as a county where 20% of the total customers were without power for at least 24 consecutive hours during the crisis, consistent with Texas PUC. We deemed 24 h a critical time-window for restoration, because within 24 h, the battery life in several types of DME would be depleted. Additionally, we conducted sensitivity analyses with a 48+ consecutive hour outage duration threshold because outages were severe state-wide, and many counties reached the 24-h threshold.

Vulnerable groups of interest
We considered six county-level measures of vulnerability: the percentage of electricity-dependent DME users, social vulnerability score, the percentage of non-Hispanic Black population, the percentage of Hispanic population, nursing homes per total population, and hospitals per total population.

DME
County-level data on electricity-dependent DME users for February, 2021 was obtained from the U.S. Department of Health and Human Services emPOWER program. emPOWER provides monthly updated information on the number of claims for one or more life-maintaining or sustaining electricity-dependent DME from Medicare Fee-for-Service and Medicare Advantage Beneficiaries [27]. We used county total number of Medicare beneficiaries from emPOWER to generate county-level percentages of DME users per Medicare beneficiaries. For each county, we estimated the number of DME users without power by multiplying the percentages of customers without power by the number of DME users in the county (Supplementary Fig. 6).

Social vulnerability
We obtained county-level data on social vulnerability from the CDC 2018 SVI. The CDC SVI is a comprehensive and validated index

designed to identify communities that may need support during disasters like the power crisis. It incorporates 15 social factors (below poverty, unemployed, income, no high school diploma, aged 65 and older, aged 17 and younger, older than age 5 with a disability, single-parent households, minority, speaks English "less than well", multi-unit structures, mobile homes, crowding, no vehicle, and group quarters), from the 2014–2018 ACS and provides an overall county vulnerability scores from 0–100 where higher values indicate increased social vulnerability [28].

Race/ethnicity

We also considered non-Hispanic Black and Hispanic populations because counties with higher percentages of non-Hispanic Black and Hispanic residents may have been disproportionately impacted by historical infrastructure underinvestment, possibly leading to reduced housing quality and grid resilience. Media articles covering the outages suggested that communities with higher Black and Hispanic populations were more likely to experience the outages [15]. Estimates of county-level counts of non-Hispanic Black and Hispanic individuals were obtained from the 2015–2019 ACS. To generate percentages, we used county total population estimates [29].

Nursing homes and hospitals

We included hospitals and nursing facilities for two reasons. Overlap between counties with severe outages and a higher presence of hospitals and/or nursing facilities were of interest because electricity is critical for these facilities to function. Conversely, overlap between counties with severe outages and a lower presence of hospitals and/or nursing facilities could worsen living conditions in already resource-deprived regions. Compiled lists of all nursing facilities and all general and specialized hospitals in Texas were obtained from the Texas Health and Human Services Commission [30, 31]. From these lists, we identified the number of facilities or hospitals in each county. We divided these values by the county total population estimates to obtain nursing homes per total population and hospitals per total population estimates. We grouped the estimates into tertiles.

Statistical analyses

We conducted statistical analyses to identify spatial correlation in power outage and social and medical factors between counties and to evaluate racial and socioeconomic disparities in exposure to the Texas Power Crisis.

Bivariate LISA

We used bivariate local indicators of association (LISA) to identify local clusters of counties with similar or different values compared to their neighbors. Bivariate LISA is a measure of spatial correlation between two variables. This is characterized by the association between the values of x in a county and the spatial lag of y (the average value of neighboring counties), where x is one of the six vulnerability variables and y is a measure of power outage. We conducted two separate bivariate LISA analyses for relative (average percentage of customers without power) and absolute (average number of customers without power) measures of power outage for each of our independent variables (the percentage of electricity-dependent DME users, CDC SVI, the percentage of non-Hispanic Black population, the percentage of Hispanic population, nursing homes per total population, and hospitals per total population). Cluster significance at the alpha level of 0.05 was determined via 99,999 permutations using the rgeoda package [32]. We used the false discovery rate to account for multiple testing [33].

Centered autologistic models

We fit two centered autologistic regression models to examine the association between each of the six vulnerability measures and the binary dependent variable measuring whether a county experienced a severe outage, on both the relative and absolute scales [34]. Centered autologistic regression is a variation of logistic regression that adjusts for spatial autocorrelation (i.e., that neighboring counties are more alike than distant counties) through the inclusion of a centered, spatially lagged y term (the average value of the neighboring counties)—the autocovariate [35]. Regression diagnostics showed that the usage of the centered autologistic model with basic binary weighting removed much of the spatial dependency observed in the residuals of the non-spatial logistic regression model (Supplementary Tables 2 and 3).

In fitting the centered autologistic models, we first examined each association overall. Next, we conducted analyses restricting to counties that fell within the ERCOT boundary (Supplementary Fig. 1). In all models, to address confounding, we a priori adjusted for county-level estimates of population density obtained from the 2015–2019 ACS and a dichotomous urban/rural classification (we considered metropolitan counties urban and non-metropolitan counties rural) [36]. 95% confidence intervals were bootstrapped with 500 samples.

Survey

Survey description. We supplemented our county-level analysis with an internet survey conducted among an existing panel of Texans to gain a better understanding of outage experience and preparedness at an individual-level. The web-based survey was deployed to adults living in Texas between March and April 2021 as a follow-up to a 2020 study that focused on environmental distress and oil and gas development [37]. In this iteration, in addition to questions on oil and gas the survey contained twelve questions pertaining to power outages and the 6-item Kessler Psychological Distress Scale [38]. Due to the original focus on oil and gas, survey participants were oversampled from the Permian Basin, the largest petroleum-producing basin in the U.S. The survey aimed to collect responses from 400 Permian Basin residents and then randomly sampled 600 residents from the rest of the state. Thus, the survey does not represent Texans overall, but does provide information related to power outage preparedness, exposure, and response. The online survey yielded 1050 responses. We excluded one respondent because they resided outside of Texas at the time of the survey and 11 (1%) respondents that reported not knowing if they experienced an outage lasting 24+ h, resulting in a final sample size of 1038.

Survey analyses. With the survey data, we focused on two main outcomes. The first, outage experience, was defined by whether a respondent reported experiencing a power outage lasting 24+ h in the prior year. The second assessed meeting the CDC definition of basic preparedness for an outage: having a working flashlight, and a 3-day supply of food and water prior to the outage. We also assessed basic preparedness after an outage.

Based on collected demographic data, we considered four different measures of vulnerability to assess disparities across outage experience and preparedness prior to outages: educational attainment (dichotomized as with/without bachelor's degree), whether someone in the household relied on DME, age (dichotomized 65+ or <65 years), and the respondents self-reported primary racial/ethnic identity (White or Caucasian, Black or African American, Hispanic or Latino, or other).

We assessed the relationship between each vulnerability measure and outage experience or preparedness separately using generalized linear mixed models (GLMM). We included an additional GLMM to measure whether experiencing an outage increased future preparedness levels. A random intercept for the respondent's county of residence was included to account for within-county correlation [39]. A priori, we included individual

characteristics: age, gender (male/female), race/ethnicity, and educational attainment; and county characteristics: population density, median household income, and urban/rural classification, which we linked to each respondent's reported county of residence. For gender, our survey had three options: "male", "female", and "gender not listed above." There were too few individuals in the third group ($n = 6$) for statistical analyses and thus they were excluded. In sensitivity analyses, we did not control for gender and present results including these six individuals (Supplementary Table 4).

To assess the relationship between measures of power outage at county and individual levels, we computed non-parametric Kendall rank correlations between the dependent variables in the county-level analysis and report of power outage from the survey. All analyses were conducted in R version 4.1.0.

RESULTS

Distribution and duration during the 2021 Texas Power Crisis

During the 2021 Texas Power Crisis (February 10–24, 2021), we estimated that customers across Texas experienced a total of 227,712,173 customer hours without power. At the peak on February 16th, this estimate totaled 4,011,776 (31%) customers in Texas, and, on average, at any time during the 2-week crisis, 645,077 (5.0%) customers were experiencing power outages.

Outage experiences including the absolute number of customers out, the percentage of customers out, and the duration of outages varied across counties (Fig. 1 and Supplementary Figs. 2–5). For most counties, the number of customers without power increased rapidly beginning February 14th or 15th before peaking and/or plateauing between February 15th and 19th (Fig. 1). Counties outside of the ERCOT boundary deviated from these trends—most non-ERCOT counties saw little to no increases in outages during the power crisis (Supplementary Fig. 1). At their peak, population dense counties like Harris, Tarrant, and Dallas counties saw 377,327 (17.5%), 367,964 (38.8%), and 358,554 (28.8%) customers without power, respectively, while 20 counties

never had more than 30 customers without power at any point in the crisis. We estimated that, at their peak, urban counties including Bexar and Tarrant had 3000+ electricity-dependent DME users without power and rural counties, including Kerr and Henderson had 400+ (Supplementary Fig. 6). Fifteen counties accounted for well over half the number of customers without power at any given hour between February 15th and 19th (Fig. 1). Intuitively, these 15 counties mostly include the 15 most populous counties in Texas with the exception of El Paso, which falls outside of the ERCOT grid and had its power plants weatherized following outages in 2011 [40]. Power outages were resolved in most counties by February 20th.

The counties with the highest percentages of customers without power, however, did not follow the same distribution; this is apparent in Fig. 2, which highlights which counties met the severe relative (1) and absolute (2) outage definitions. Instead, it was suburban and rural counties with the largest percentages of customers without power and for the longest durations (Fig. 2 and Supplementary Fig. 5). Less densely populated counties saw high percentages of customers without power throughout the crisis, rather than only on the most heavily impacted days (Supplementary Fig. 5).

Bivariate LISA analyses revealed spatial clustering between power outages and vulnerable groups for counties near the Texas-Mexico border and the Gulf coast (Supplementary Figs. 7 and 8). The spread and duration of outages varied across county characteristics (Table 1). In centered autologistic regressions, we observed an association between increased percentages of Hispanic individuals and higher odds of 10,000 people in the county being without power for both 24+ (Table 2) and 48+ h (Supplementary Table 5). An association between increased percentages of Hispanic individuals and odds of 20% of customers in the county being without power was only observed in sensitivity analysis using the 48+ h time window (Supplementary Table 5). We observed a negative association between the percentage of electricity-dependent DME users and severe outages in both absolute and relative models.
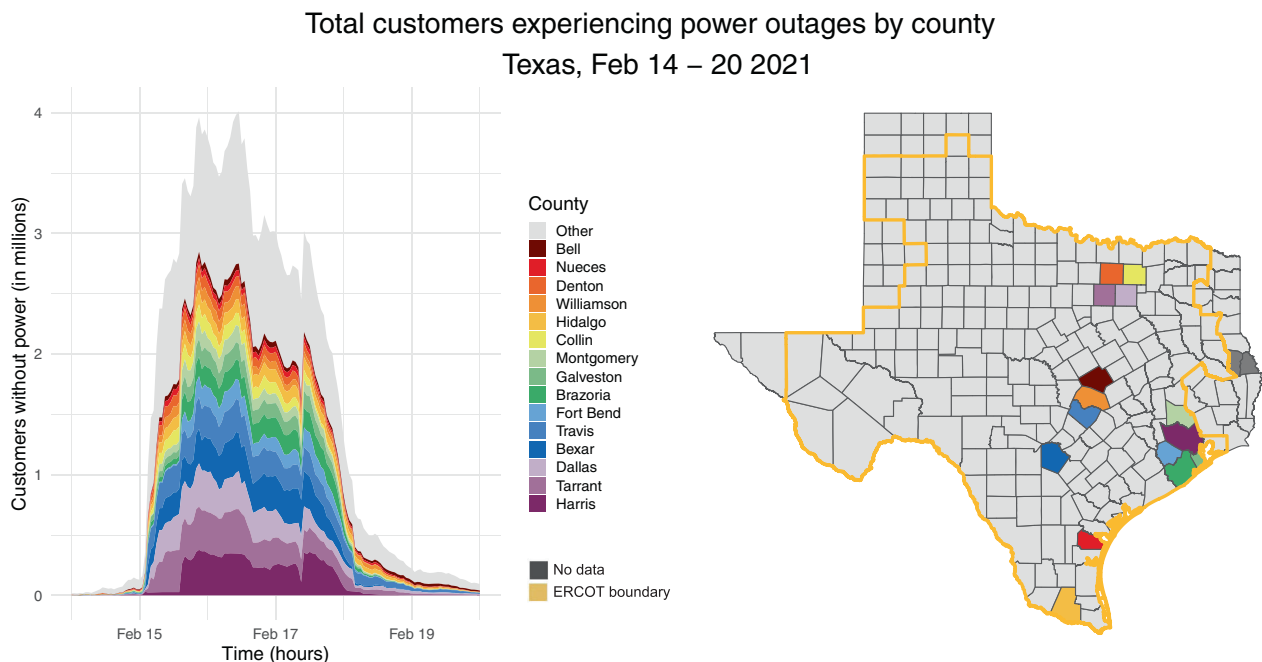

Total customers experiencing power outages by county
Texas, Feb 14 – 20 2021

Fig. 1 Total customers experiencing power outages. We provide an hourly stacked area plot between February 14–19, 2021 with a corresponding map. The 15 counties that contributed the most person-hours without power are shown in color. Counties in plot are ordered by maximum number of customers without power with the counties that had the highest number without power on the bottom. In the corresponding map, the ERCOT boundary is overlaid (yellow).

Consecutive hours with 20%+ or 10,000+ customers without power by county
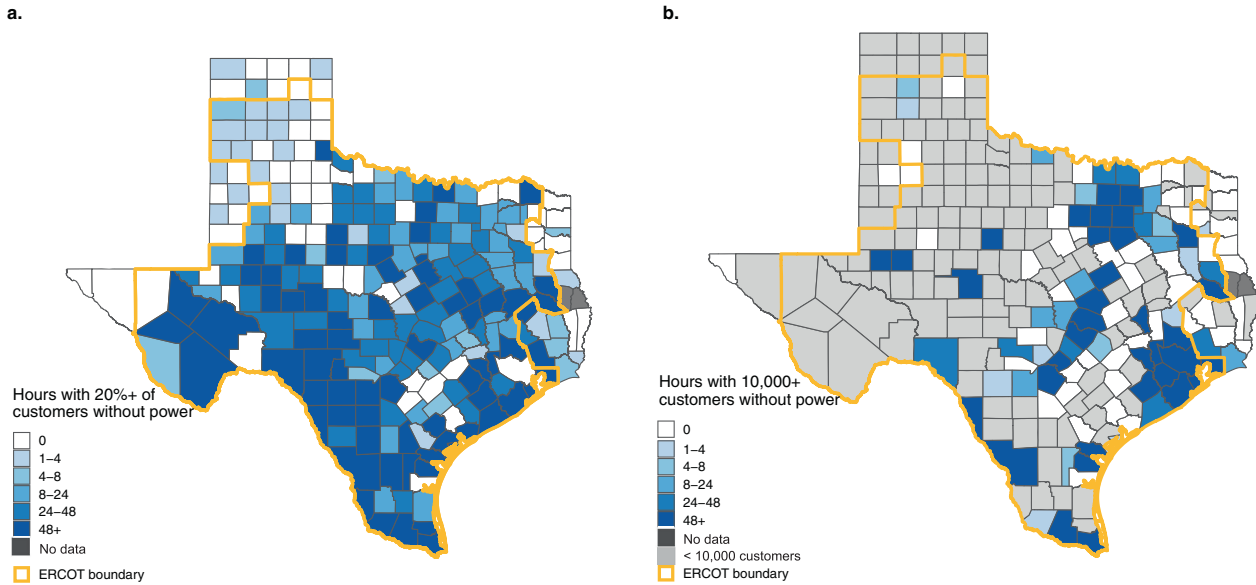Texas, February 10 – 24, 2021

Fig. 2 County-level distribution and duration of power outages. We depict the range in consecutive hours that **a** 20% of customers, or **b** 10,000 customers in a county were without power between February 10–24, 2021. Darker blues indicate longer outage durations. We overlaid the ERCOT boundary (yellow).

Table 1. County characteristics overall and by power outage experiences in Texas.

Characteristic	Overall (*n* = 252[a])	Among counties that experienced severe outage for 24+ h	
		Definition of severe outage	
		Relative (20% without power, *n* = 119)	Absolute (10,000 without power, *n* = 45)[b]
DME use per Medicare beneficiaries—Median (IQR)	5.21 (4.08, 6.61)	4.48 (3.76, 5.41)	3.82 (3.22, 4.67)
SVI score—Median (IQR)	0.5 (0.3, 0.8)	0.5 (0.3, 0.8)	0.3 (0.2, 0.7)
Percent Black residents—Median (IQR)	3.6 (1.0, 8.9)	3.1 (0.8, 8.8)	7.8 (3.6, 13.5)
Percent Hispanic residents—Median (IQR)	27.3 (18.6, 50.5)	28.6 (21.2, 52.5)	26.8 (22.4, 42.5)
Nursing homes per 100,000 population—N(%)			
Low (0–5.9]	84 (33.3)	45 (42.4)	29 (64.4)
Med (5.9, 11.7]	84 (33.3)	37 (34.9)	16 (36.6)
High (11.7, 155]	84 (33.3)	37 (34.9)	0 (0)
Hospitals per 100,000 population—N(%)			
Low (0–1.4]	84 (33.3)	37 (34.9)	8 (17.8)
Med (1.4, 4.8]	84 (33.3)	45 (42.4)	33 (73.3)
High (4.8, 69.6]	84 (33.3)	37 (34.9)	4 (8.9)
Population density—Median (IQR)	8.6 (2.4, 25.4)	8.7 (2.7, 37.1)	89 (31.4, 192)
Urban/rural classification—N(%)			
Urban	82 (33.5)	46 (38.7)	37 (82.2)
Rural	170 (67.5)	73 (61.3)	9 (17.8)
Grid classification—N(%)			
ERCOT	213 (84.5)	116 (97.5)	44 (97.8)
Non-ERCOT	41 (15.5)	3 (2.5)	1 (2.2)

DME durable medical equipment, *ERCOT* Electric Reliability Council of Texas, *SVI* CDC Social Vulnerability Index.
[a]Sabine and San Augustine excluded due to missing outage data.
[b]Among counties with at least 10,000 customers (*n* = 115).

Individual-level experience of power outage and preparedness

Using data from a previous internet survey that oversampled participants from the Permian Basin, we had responses from individuals (*N* = 1038) residing in 116 of the 254 counties within Texas. Approximately half (*n* = 545 [52.5%]) of the respondents

reported experiencing a "severe" outage lasting 24+ h in the past year. Descriptively, having experienced a severe outage differed across groups, for example, those who experienced an outage were more likely to be Black or African American (15% vs. 8.1%, Table 3). Those who experienced an outage were also more likely to meet the clinically significant threshold for distress (26% vs.

Table 2. County-level analyses: adjusted centered autologistic model results for associations between outage experience and vulnerability measures.

Variable	Centered autologistic results—OR (95% CI)	
	Power outage definition	
	Relative (20% without power)	**Absolute (10,000+ without power)[a]**
Overall[b]		
Per 1-unit increase		
DME use per Medicare beneficiaries	0.82 (0.61, 0.98)	0.50 (0.21, 0.83)
SVI score	0.82 (0.19, 2.85)	1.37 (0.23, 12.15)
Per 5-unit increase		
Percent Black residents	0.95 (0.67, 1.38)	0.91 (0.51, 1.47)
Percent Hispanic residents	0.94 (0.84, 1.05)	1.16 (1.02, 1.40)
Nursing homes per total population	–	–
Med	0.99 (0.41, 2.27)	0.51 (0.13, 1.73)
High	1.96 (0.78, 5.05)	Not estimated[d]
Hospitals per total population	–	–
Med	1.62 (0.73, 3.67)	2.08 (0.65, 10.58)
High	1.39 (0.60, 3.16)	1.98 (0.22, 20.21)
ERCOT only[b,c]		
Per 1-unit increase		
DME use per Medicare beneficiaries	0.81 (0.60, 0.97)	0.61 (0.18, 1.08)
SVI score	0.88 (0.22, 3.49)	2.70 (0.12, 69.34)
Per 5-unit increase		
Percent Black residents	1.21 (0.78, 1.93)	1.03 (0.42, 2.59)
Percent Hispanic residents	0.92 (0.81, 1.05)	1.23 (1.02, 1.66)
Nursing homes per total population	–	–
Med	1.19 (0.47, 2.81)	0.60 (0.11, 3.33)
High	2.17 (0.85, 5.79)	Not estimated[d]
Hospitals per total population	–	–
Med	1.56 (0.73, 3.94)	1.96 (0.31, 26.31)
High	1.42 (0.63, 3.12)	6.74 (0.47, 212.72)

OR odds ratio, 95% CI 95% confidence interval, DME Durable Medical Equipment, SVI CDC Social Vulnerability Index.
[a]Each absolute model was conducted among counties with at least 10,000 customers (n = 115).
[b]Adjusted for population density and urban/rural classification.
[c]Restricted to counties within the ERCOT boundary.
[d]Not estimated due to no observations in this class.

17%). Among those who experienced a severe outage, 272 (50%) reported experiencing health-related anxiety, 189 (35%) reported that they had to evacuate due to the outage, and only 243 (45%) reported meeting basic preparedness guidelines by having a working flashlight and 3-day supplies of food and water prior to the outage. The most cited experience during an outage was discomfort from cold after loss of heating (N = 444 [81.5%]). Loss of heat was also the most cited reason for evacuation during an outage (N = 167 [30.6%], Supplementary Fig. 9). The majority (N = 310 [57%]) of respondents experiencing outages received no notice that an outage would occur, with older adults the most likely to report not receiving any notice (N = 31[66%], Supplementary Table 6).

In regression analyses, we assessed associations between individual-level vulnerability factors: age, educational attainment, race/ethnicity, and household use of DME, and power outage experience and preparedness. Age 65+ was associated with reduced odds of experiencing a severe outage and increased odds of preparedness prior to the outage (Table 4). Household use of DME was related to 2x higher odds of experiencing a severe outage but no increase in preparedness. We found no relationship between primary racial/ethnic identity and preparedness;

however, Black or African American race was associated with 1.7x higher odds of experiencing a severe outage compared to White or Caucasian respondents. We also found no relationship between educational attainment and outage experience; however, lower educational attainment was associated with reduced odds of preparedness. Experiencing a past outage was related to increased future preparedness.

In ranked correlation tests, we found no association between survey-reported experience of a severe outage and the relative severe outage dependent variable (20% of county without power for at least 24 h, Kendall's tau = −0.01, p = 0.67) and a weak, positive association between the survey data and the absolute severe outage dependent variable (10,000+ customers without power for 24+ h, Kendall's tau = 0.16, p < .001).

DISCUSSION

The 2021 Texas Power Crisis devastated the state, collectively causing 228,542,027 customer hours without power. Using utility data, we found an uneven burden of power outage distribution, magnitude, and duration. Fifty-eight (23%) counties experienced 48+ h where ≥20% of customers lacked power; 64 (25%) counties

Table 3. Individual surveys: demographic characteristics and outage experience.

	Overall, $n = 1038$ n (%)	Experienced power outage lasting 24+ h in past year		
		No, $n = 493$ n (%)	Yes, $n = 545$ n (%)	P value
Gender				0.3[a]
Man	494 (47.6)	242 (49)	252 (46.2)	
Woman	538 (51.8)	250 (50.8)	288 (52.8)	
Gender not listed above	6 (0.6)	1 (0.2)	5 (0.9)	
Primary racial or ethnic identity				0.008[a]
American Indian or Alaskan Native	8 (0.8)	4 (0.8)	4 (0.7)	
Asian	50 (4.8)	26 (5.3)	24 (4.4)	
Black or African American	121 (12)	40 (8.1)	81 (15)	
Hispanic or Latino	233 (22)	104 (21)	129 (24)	
Native Hawaiian or Pacific Islander	5 (0.5)	2 (0.4)	3 (0.6)	
White or Caucasian	609 (59)	314 (64)	295 (54)	
Other	9 (0.9)	3 (0.6)	6 (1.1)	
Age group				0.002[b]
18–24	154 (14.9)	63 (12.8)	91 (16.7)	
25–34	228 (22)	97 (19.7)	131 (24)	
35–44	200 (19.2)	97 (19.7)	103 (18.9)	
45–54	157 (15.1)	68 (13.8)	89 (16.3)	
55–64	171 (16.5)	86 (17.5)	85 (15.6)	
65 or older	128 (12.3)	81 (16.5)	47 (8.6)	
Education				0.13[b]
Less than high school diploma	46 (4.4)	24 (4.9)	22 (4.0)	
High school degree or equivalent (e.g., GED)	233 (22.5)	127 (25.8)	106 (19.4)	
Some college, no degree	280 (27)	123 (24.9)	157 (28.8)	
Associate degree (e.g., AA, AS)	108 (10.4)	49 (10)	59 (10.8)	
Bachelor's degree or more	371 (35.4)	170 (34.6)	201 (36.9)	
Urban/rural classification				0.048[b]
Rural	171 (16.5)	93 (18.9)	78 (14.3)	
Urban	867 (83.5)	400 (81.1)	467 (85.7)	
Someone in household relies on electricity-dependent DME				<0.001[b]
No	855 (82.4)	429 (87.2)	426 (78.2)	
Yes	166 (16)	58 (11.8)	108 (19.3)	
Do not know	16 (1.5)	5 (1.0)	11 (2.0)	
K-6 distress scale score				<0.001[b]
Less than 13	746 (79)	378 (83)	368 (74)	
13 or higher	203 (21)	76 (17)	127 (26)	

[a]Fisher's exact test.
[b]Pearson's Chi-squared test.

never reached 20% of customers without power. We observed no socioeconomic differences in power outage duration or magnitude at the county-level, while counties with a higher proportion of Hispanic residents had higher counts and proportions of customers without power for a prolonged period. Counties with a higher proportion of Medicare DME users had less severe power outage experiences. With internet survey data that oversampled participants in the Permian oil and gas basin, we found that individuals using DME had 2x the odds of experiencing a 24+ h power outage in the prior year (vs. non-DME users), demonstrating the utility of combining multiple data streams to assess disparities. While not representative of the general Texas population, survey data also indicated that individual DME users were also no more likely than the average respondent to meet basic power outage preparedness guidelines, that less educated participants had lower levels of preparedness, that preparedness increased following experience of a major outage, and that older adults had the least advanced warning about outages.

We found no difference in outage severity or duration by county-level hospital or nursing home rates, which few studies have investigated. A study of a single utility serving an American Indian community found increased outage durations in block groups regarding furthest from the nearest hospital [10]. Another study in Phoenix, Arizona similarly found that outage durations increased

Table 4. Associations between survey respondents' demographics and outage experiences or preparedness.

Outcome	Variable	Odds ratio (95% confidence interval)[a]
Experienced power outage lasting 24+ h in past year	Educational attainment	
	Bachelors degree or more	–
	Less than bachelors degree	0.82 (0.61, 1.10)
	Electricity-dependent medical device usage	
	No household DME use	–
	Household DME use	1.95 (1.33, 2.85)
	Age	
	Less than 65 years	–
	65+	0.52 (0.34, 0.79)
	Primary racial/ethnic identity	
	White or Caucasian	–
	Black or African American	1.67 (1.06, 2.61)
	Hispanic or Latino	1.15 (0.81, 1.64)
	Other[b]	0.83 (0.49, 1.44)
Met basic preparedness prior to outage experience	Educational attainment	
	Bachelors degree or more	–
	Less than bachelors degree	0.68 (0.46, 1.01)
	Electricity-dependent medical device usage	
	No household DME use	–
	Household DME use	1.00 (0.63, 1.57)
	Age	
	Less than 65 years	–
	65+	2.50 (1.27, 4.90)
	Primary racial/ethnic identity	
	White or Caucasian	–
	Black or African American	0.92 (0.54, 1.57)
	Hispanic or Latino	0.81 (0.50, 1.30)
	Other[b]	1.24 (0.60, 2.57)
Met basic preparedness at time of survey	Experienced power outage lasting 24+ h in past year	
	No	–
	Yes	1.53 (1.16, 2.03)

DME durable medical equipment.
[a]Adjusted for county-level characteristics: urban/rural classification, populations density, and median household income and individual-level characteristics: age, gender, educational attainment, and primary racial/ethnic identity.
[b]Other includes American Indian or Alaskan Native, Asian, Native Hawaiian or Pacific Islander, and Other primary racial/ethnic identity categories.

with distance from the nearest hospital [41]. The PUC of Texas requires power restoration prioritization for customers deemed critical for public safety, including hospitals [42]. Because historical policies may result in wealthier communities having greater access to resources like hospitals, emphasizing power restoration near community assets could drive inequitable power outages. We did not observe this phenomenon at the county-level for hospitals or nursing facilities, consistent with the Rockefeller report that used block group-level data [14]. This lack of a relationship may be explained by aggregated data (county or census block groups), which can cause spatial misclassification. Likely more important was the sweeping nature of the Texas Power Crisis, potentially making preferential re-powering impossible.

We identified worse outages among counties with a higher percent of Hispanic residents, consistent with prior research on racial/ethnic disparities in outage experience. In Florida, Mitsova et al. reported longer power restoration times to Hispanic communities after Hurricane Irma, using snapshots of outage coverage each morning for 3 weeks [9]. Similarly, a 2020 Texas-based study interviewing 1052 Harris County residents found that reported outage durations after Hurricane Harvey were longer for non-White vs. White respondents [43]. However, not all surveys find disparities. Interviews with 584 patients impacted by Hurricane Sandy found that power outages lasted longer for non-Hispanic White vs. Black and Hispanic individuals [37]. Related to the 2021 Texas Crisis, a Rockefeller report using nighttime satellite data to identify block groups without power, found that in census block groups with higher percentages of non-White populations, larger shares of the population experienced outages [14]. Among participants in our internet survey, Black vs. White

respondents were more likely to report experiencing a prolonged outage. The present study fits into a growing body of climate EJ literature finding that environmental exposures disproportionately burden Black and Hispanic U.S. populations [44].

We did not identify differences in outages by county-level SES or resource deprivation. Despite our results, disparities could still exist at finer spatial scales. The Rockefeller report identified block group-level disparities in power outage exposure during the crisis by racial/ethnic composition and poverty, though disparities were larger by race/ethnicity [14]. Our individual-level survey did not find evidence of socioeconomic differences in exposure, but provided some evidence for socioeconomic differences in preparedness, with less educated respondents less likely to be prepared for an outage. This is consistent with evidence that socioeconomic barriers may hinder preparing for outages [45, 46].

Of the vulnerable subgroups studied, electricity-dependent DME users likely face the greatest health risks during power outages, particularly when outages lead to medical device failure. Studies have shown increased healthcare utilization among DME users during outages [6]. We consistently found that counties with higher percentages of electricity-dependent Medicare DME users had lower outage prevalence which may reflect two patterns: (1) there was lower outage severity in areas such as the panhandle where a greater proportion of Medicare electricity-dependent DME users reside and (2) lower proportions of Medicare DME use among south Texas communities where severe outages occurred. This second pattern may reflect higher percentages of persons without citizenship in this region who may not qualify for Medicare (Supplementary Fig. 10). The emPOWER dataset includes all Medicare recipients, 93.5% of adults aged 65+ in 2020 [47]. Vulnerable individuals, including those under the age of 65 who do not qualify for Medicare via disability benefits, but may use DME are not represented; this is a limitation to the emPOWER dataset. Though the Texas PUC aims to prioritize power restoration to life-sustaining DME users [42], further inquiry is needed to understand whether this prioritization is effective in application—especially since targeted power restoration was nearly impossible during the massive outages of February 2021. While county-level data indicated less outage exposure among higher DME prevalence counties, our individual surveys highlighted possible disparities in exposure and preparedness; surveyed households where someone relied on DME were nearly 2x as likely to report experiencing a 24+ h outage in the prior year and were no more likely to meet CDC basic preparedness guidelines than other households. Unlike Medicare data, our surveys captured individuals of any age relying on DME, one reason we may observe a different relationship. Prior studies have found limited preparedness among DME using families [48]. Even after a statewide campaign for disaster preparedness in Pennsylvania, only 77% of rural and 55% of urban interviewees using electricity-dependent DME had outage preparedness plans [49], highlighting the need for greater understanding of the barriers (socioeconomic, awareness, resource deprivation) to preparedness among DME users, a group expected to increase in size in the future [27].

Using bivariate LISA analyses, we identified regions with significant overlap between power outages and vulnerability. We analyzed vulnerable groups separately, but due to underlying social structures in the U.S., they likely overlap. For example, research documents a higher prevalence of DME usage among lower SES populations [50]. The counties (e.g., Harris—city of Houston, Val Verde, Kimble) that appeared in multiple bivariate clusters provide evidence of the correlated and compounding socioeconomic, demographic, and community-level factors that may increase vulnerability to power outages and climate change.

Several limitations temper our results: first, we obtained our outage data from PowerOutage.US, which pulls outage information directly from utilities, meaning customer counts are only as accurate as utilities report them. Second, several utilities did not report the number of customers served, and in these cases, we estimated the count using census data, assuming customer counts followed total household estimates. Third, because of data availability, we conducted county-level analyses. This introduces bias by ignoring within-county variation; such variation was evident when comparing individual and county-level results. Fourth, we surveyed a small sample of Texans, living 116 of the 254 Texas counties—with oversampling in the Permian Basin. Our survey also obtained individual self-reported primary race/ethnicity using a different scheme than the US Census, further limiting comparability between our county-level and survey results. We also queried respondents about major power outages in the past year, so respondents could refer to outages outside the Crisis. Further, the SES covariates adjusted for in the survey analyses may have mediated the relationship between race and outage experience/preparedness, and age and outage experience/preparedness. We retained these variables in the model to ensure that the observed relationship was not driven by SES, and thus may have underestimated effects. Survey results should not be generalized to all Texans. Instead, these results should be interpreted as exploratory insights into the ways that power outages can impact groups differently based on their preparedness and access to resources. Finally, we were unable to link either our county- or individual-level analyses to direct health outcomes, an avenue for future research.

Not an anomaly, the Texas Power Crisis reflects a trend of worsening power outages in the U.S. Climate change has resulted in more frequent and severe heatwaves, heavy rains, wildfires, and winter storms [51]. These events damage aging electric grids already stressed by customer demand [52] and underinvestment [53]—making it increasingly urgent to identify subpopulations vulnerable during outages. We found that counties with higher percentages of Hispanic residents tended to experience longer and more widespread outages. Individual analyses also highlighted low preparedness levels, especially among younger and low-SES respondents. Climate and energy policy must address power outages and consider socially, politically, economically, and medically vulnerable groups.

DATA AVAILABILITY
The final dataset used in the county-level analysis including customers without power, customers served, and the demographic information is available on GitHub (https://github.com/nina-flores/texas-po-dta). The code used for county-level analyses are also available. Individual-level data from analyses may be available following IRB approval.

REFERENCES
1. Busby JW, Baker K, Bazilian MD, Gilbert AQ, Grubert E, Rai V, et al. Cascading risks: understanding the 2021 winter blackout in Texas. Energy Res Soc Sci. 2021;77:102106.
2. Texas Department of State Health Services. Winter storm-related deaths: Texas Department of State Health Services. 2021. https://dshs.texas.gov/news/updates.shtm.
3. Aldhous P, Lee SM, Hirji Z. The texas winter storm and power outages killed hundreds more people than the state says: BuzzFeed News. 2021. https://www.buzzfeednews.com/article/peteraldhous/texas-winter-storm-power-outage-death-toll.
4. Cohen J, Pfeiffer K, Francis JA. Warm Arctic episodes linked with increased frequency of extreme winter weather in the United States. Nat Commun. 2018;9:869.
5. Casey JA, Fukurai M, Hernández D, Balsari S, Kiang MV. Power outages and community health: a narrative review. Curr Environ Health Rep. 2020;7:371–83.
6. Molinari NAM, Chen B, Krishna N, Morris T. Who's at risk when the power goes out? The at-home electricity-dependent population in the United States, 2012. J Public Health Manag Pr. 2017;23:152–9.

7. Smith GS, Anjum E, Francis C, Deanes L, Acey C. Climate change, environmental disasters, and health inequities: the underlying role of structural inequalities. Curr Environ Health Rep. 2022;9:80–9.

8. Chakraborty J, McAfee AA, Collins TW, Grineski SE. Exposure to Hurricane Harvey flooding for subsidized housing residents of Harris County, Texas. Nat Hazards. 2021;106:2185–205.

9. Mitsova D, Esnard A-M, Sapat A, Lai BS. Socioeconomic vulnerability and electric power restoration timelines in Florida: the case of Hurricane Irma. Nat Hazards. 2018;94:689–709.

10. Maliszewski PJ, Larson EK, Perrings C. Environmental determinants of unscheduled residential outages in the electrical power distribution of Phoenix, Arizona. Reliab Eng Syst Saf. 2012;99:161–71.

11. Liévanos RS, Horne C. Unequal resilience: the duration of electricity outages. Energy Policy. 2017;108:201–11.

12. Román MO, Stokes EC, Shrestha R, Wang Z, Schultz L, Carlo EAS, et al. Satellite-based assessment of electricity restoration efforts in Puerto Rico after Hurricane Maria. PLoS ONE. 2019;14:e0218883.

13. Dvorkin Y. How to Prevent a Power Outage From Becoming a Crisis: @. 2021. https://spectrum.ieee.org/prevent-power-outage-crisis.

14. Carvallo J, Hsu FC, Shah Z, Taneja J. Frozen out in Texas: blackouts and inequity—The Rockefeller Foundation. The Rockefeller Foundation; 2021. https://www.rockefellerfoundation.org/case-study/frozen-out-in-texas-blackouts-and-inequity/.

15. Garnham AU, Juan P. Already hit hard by pandemic, Black and Hispanic communities suffer the blows of an unforgiving winter storm. 2021.

16. Baker S, DeVar S, Prakash S. Section 1—Defining Energy Justice: Connections to Environmental Justice, Climate Justice, and the Just Transition—Initiative for Energy Justice. 2019.

17. Gonzalez DJX, Nardone A, Nguyen AV, Morello-Frosch R, Casey JA. Historic redlining and the siting of oil and gas wells in the United States. J Expo Sci Environ Epidemiol. 2022:1–8.

18. Lewis J, Hernández D, Geronimus AT. Energy efficiency as energy justice: addressing racial inequities through investments in people and places. Energy Efficiency. 2020;13:419–32.

19. Hernández D. Understanding 'energy insecurity' and why it matters to health. Soc Sci Med. 2016;167:1–10.

20. Jessel S, Sawyer S, Hernández D. Energy, poverty, and health in climate change: a comprehensive review of an emerging literature. Front Public Health. 2019;7:1–16.

21. "Maps." Electric Reliability Council of Texas (ERCOT). 2021. http://www.ercot.com/news/mediakit/maps.

22. Galbraith K. Texplainer: why does Texas have its own power grid? 2011.

23. Dominianni C, Lane K, Johnson S, Ito K, Matte T. Health impacts of citywide and localized power outages in New York City. Environ Health Perspect. 2018;126:067003.

24. Mukherjee S, Nateghi R, Hastak M. A multi-hazard approach to assess severe weather-induced major power outage risks in the US. Reliab Eng Syst Saf. 2018;175:283–305.

25. Zhang W, Sheridan S, Birkhead G, Croft D, Brotzge J, Justino J, et al. Power outage: an ignored risk factor for chronic obstructive pulmonary disease exacerbations. Chest. 2020;158:2346–57.

26. Project 40296. Public Utility Commission of Texas. 2012.

27. HHS emPOWER Program. 2021. https://empowerprogram.hhs.gov/about-empowermap.html.

28. CDC/ATSDR Social Vulnerability Index: Centers for Disease Control and Prevention/Agency for Toxic Substances and Disease Registry/Geospatial Research, Analysis, and Services Program. 2018. https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html.

29. Manson S, Schroeder J, Van Riper D, Kugler T, Ruggles S. IPUMS National Historical Geographic Information System: Version 16.0 [dataset]. Minneapolis, MN: IPUMS; 2021. https://doi.org/10.18128/D050.V16.0.

30. Texas Health and Human Services. Nursing Facilities (NF). Texas Health and Human Services. 2021. https://www.hhs.texas.gov/doing-business-hhs/provider-portals/long-term-care-providers/nursing-facilities-nf.

31. Texas Health and Human Services. Hospitals—Directory of General and Special Hospitals. Texas Health and Human Services. 2021. https://www.hhs.texas.gov/doing-business-hhs/provider-portals/health-care-facilities-regulation/hospitals-general-hospitals.

32. Li X, Anselin L. rgeoda: R Library for Spatial Data Analysis. 2022. https://github.com/geodacenter/rgeoda/, https://geodacenter.github.io/rgeoda/.

33. Korthauer K, Kimes PK, Duvallet C, Reyes A, Subramanian A, Teng M, et al. A practical guide to methods controlling false discoveries in computational biology. Genome Biol. 2019;20:118.

34. Caragea PC, Kaiser MS. Autologistic models with interpretable parameters. J Agric Biol Environ Stat. 2009;14:281.

35. Besag JE. Nearest-neighbour systems and the auto-logistic model for binary data. J R Stat Soc Series B Methodol. 1972;34:75–83. http://www.jstor.org/stable/2985051.

36. Ingram DD, Franco SJ. NCHS urban–rural classification scheme for counties. National Center for Health Statistics. Vital Health Stat 2. 2014;166:1–5.

37. Elser H, Goldman-Mellor S, Morello-Frosch R, Deziel NC, Ranjbar K, Casey JA. Petro-riskscapes and environmental distress in West Texas: community perceptions of environmental degradation, threats, and loss. Energy Res Soc Sci. 2020;70:101798.

38. Kessler RC, Barker PR, Colpe LJ, Epstein JF, Gfroerer JC, Hiripi E, et al. Screening for serious mental illness in the general population. Arch Gen Psychiatry. 2003;60:184–9.

39. Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, et al. Generalized linear mixed models: a practical guide for ecology and evolution. Trends Ecol Evolution. 2009;24:127–35.

40. Juarez S. El Paso Heeded the Warnings and Avoided a Winter Catastrophe. TexasMonthly. 2021.

41. Maliszewski PJ, Perrings C. Factors in the resilience of electrical power distribution infrastructures. Appl Geogr. 2012;32:668–79.

42. PUC T. 25.497—Critical Load Industrial Customers, Critical Load Public Safety Customers, Critical Care Residential Customers, and Chronic Condition Residential Customers. Public Utility Commission of Texas. 2018.

43. Coleman N, Esmalian A, Mostafavi A. Equitable resilience in infrastructure systems: empirical assessment of disparities in hardship experiences of vulnerable populations during service disruptions. Nat Hazards Rev. 2020;21:04020034.

44. EPA. Climate change and social vulnerability in the United States: a focus on six impacts. U.S. Environmental Protection Agency, EPA 430-R-21-003. 2021.

45. Dominianni C, Ahmed M, Johnson S, Blum M, Ito K, Lane K. Power outage preparedness and concern among vulnerable New York City residents. J Urban Health. 2018;95:716–26.

46. Cox K, Kim B. Race and income disparities in disaster preparedness in old age. J Gerontol Soc Work. 2018;61:719–34.

47. Keisler-Starkey K, Bunch LN. Health insurance coverage in the United States. 2020.

48. Sakashita K, Matthews WJ, Yamamoto LG. Disaster preparedness for technology and electricity-dependent children and youth with special health care needs. Clin Pediatrics. 2013;52:549–56.

49. Zidek C, West E, Holmes J, Crytzer M. A survey comparison of rural versus urban residents and household preparedness. Home Healthcare Now. 2014;32:420–9.

50. Casey JA, Mango M, Mullendore S, Kiang MV, Hernández D, Li BH, et al. Trends from 2008 to 2018 in electricity-dependent durable medical equipment rentals and sociodemographic disparities. Epidemiology. 2021;32:327–35.

51. IPCC. Climate Change 2021: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. In: Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, et al. editors. Cambridge University Press. In Press. 2021.

52. Pressler M. Texas Electricity in 2021. 2021.

53. American Society of Civil Engineers. 2021 report card for America's infrastructure: funding and future need. 2021.

ADDITIONAL INFORMATION

Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s41370-022-00462-5.

Correspondence and requests for materials should be addressed to Nina M. Flores.

Reprints and permission information is available at http://www.nature.com/reprints