PLOS CLIMATE

RESEARCH ARTICLE

Powerless in the storm: Severe weather-driven power outages in New York State, 2017–2020

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OPEN ACCESS

Citation: Flores NM, Northrop AJ, Do V, Gordon M, Jiang Y, Rudolph KE, et al. (2024) Powerless in the storm: Severe weather-driven power outages in New York State, 2017–2020. PLOS Clim 3(5): e0000364. https://doi.org/10.1371/journal.pclm.0000364

Editor: Teodoro Georgiadis, Institute for BioEconomy CNR, ITALY

Received: October 31, 2023

Accepted: February 2, 2024

Published: May 1, 2024

Peer Review History: PLOS recognizes the benefits of transparency in the peer review process; therefore, we enable the publication of all of the content of peer review and author responses alongside final, published articles. The editorial history of this article is available here: https://doi.org/10.1371/journal.pclm.0000364

Data Availability Statement: Meteorological and social variables were obtained from publicly available datasets described in the methods section. Power outage data was obtained from the

Abstract

The vulnerability of the power grid to severe weather events is a critical issue as climate change is expected to increase extreme events, which can damage components of the power grid and/or lessen electrical power supply, resulting in power outages. However, largely due to an absence of granular spatiotemporal outage data, we lack a robust understanding of how severe weather-driven outages, their community impacts, and their durations distribute across space and socioeconomic vulnerability. Here, we pair hourly power outage data in electrical power operating localities (n = 1865) throughout NYS with urbanicity, CDC Social Vulnerability Index, and hourly weather (temperature, precipitation, wind speed, lightning strike, snowfall) data. We used these data to characterize the impact of extreme weather events on power outages from 2017–2020, while considering neighborhood vulnerability factors. Specifically, we assess (a) the lagged effect of severe weather on power outages, (b) common combinations of severe weather types contributing to outages, (c) the spatial distribution of the severe weather-driven outages, and (d) disparities in severe weather-driven outages by degree of community social vulnerability. We found that across NYS, 39.9% of all outages co-occurred with severe weather. However, certain regions, including eastern Queens, upper Manhattan and the Bronx of NYC, the Hudson Valley, and Adirondack regions were more burdened with severe weather-driven outages. Using targeted maximum likelihood estimation, we found that the frequency of heat-, precipitation-, and wind-driven outages disproportionately impacted vulnerable communities in NYC. When comparing durations of outages, we found that in rural regions, precipitation- and snow-driven outages lasted the longest in vulnerable communities. Under a shifting climate, anticipated increases in power outages will differentially burden communities due to regional heterogeneity in severe weather event severity, grid preparedness, and population

NYS Department of Public Service: https://dps.ny.gov/electric.

Funding: This work was supported by the National Institute for Environmental Health Sciences (NIEHS) P30 ES009089 (JAC), 5T32ES007322-22 (NMF), and P30ES007033 (JAC). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

socioeconomic profiles/vulnerabilities. As such, policymakers must consider these characteristics to inform equitable grid management and improvements.

Introduction

Electricity is a critical aspect of modern life, supporting everyday activities like making a phone call, cooking a meal, and heating or cooling one's home [1, 2]. Despite how central electricity is to daily life, having resilient and reliable power systems remains a challenge in the United States (US) [2]. Power outages (POs) are becoming increasingly common–in large part due to the age and disrepair of the electrical grid and its vulnerability to severe weather events. Severe weather, the leading cause of widespread power outages in the US [3–5], can lead to cascading effects such as throwing key parameters of power quality like frequency or voltage out of sync, overloading transmission lines, or even complete voltage/frequency collapse [5]. A range of severe weather conditions threaten the grid, including extreme heat, extreme cold, and tropical storms. For example, the Chicago Heat Wave of 1995 led to a surge in power use and the failure of three power transformers. This led to widespread outages for over two days [6]. In 2012, Hurricane Sandy downed overhead lines and flooded underground lines, leading to extensive outages, sometimes lasting weeks and affecting millions of customers across 21 Northeastern states [7]. In Texas, Winter Storm Uri in 2021 froze natural gas wells, power plants, and gathering lines, leaving millions of customers without power for days to weeks [8].

The power grid's vulnerability to severe weather events becomes even more critical in the context of climate change, which is expected to increase weather variability and prevalence of extreme events (e.g., storms, wildfires, heatwaves, floods) [9]. Such events readily damage components of the power grid including power plants, substations, distribution centers, and power lines. In addition to causing more extreme events, climate change will result in rising temperatures and increased temperature variability, affecting electricity reliability and use. High temperatures can decrease the output from thermoelectric plants and the carrying capacity of power lines, but also increase the power demand as people run air conditioning to keep cool [10, 11]. The energy transition will result in greater reliance on electricity for heating, cooking, and transit, making continuous access increasingly vital [12]. Outages, especially those occurring with very hot or cold weather have been tied to adverse cardiovascular, respiratory, and renal outcomes [13]. Thus, preventing prolonged outages or providing backup power sources is critical for population health.

Climate-driven increases in power outages raise important environmental and climate justice concerns. Persistently marginalized communities may already be disproportionately burdened by severe weather-driven outages due to a confluence of factors such as discriminatory housing practices [14], historic underfunding in communities of color, inequitable restoration guidelines [15, 16], and the concentration of low-income communities and communities of color high-risk areas like flood zones [17] and hot neighborhoods [18, 19]. Researchers cataloged exposure disparities during some outages [20, 21]. Outages in New York City resulting from Tropical Storm Isaias were longer in regions that were lower income and/or had higher percentages of non-white residents [22]. Thus, documenting the dual burden of extreme events and power outage exposure is necessary to promote health equity. However, previous assessments of severe weather-driven outages (a) rarely included data at a sub-county level; and (b) often failed to consider urban/rural differences for which outages may have varying community impacts due to population/housing density, demographic profiles and/or backup power accessibility [3, 4, 13]. Such analyses could inform policies related to electrical grid reliability and restoration to promote health equity.

New York State (NYS), however, collects power outage data statewide at a granular (~zip code tabulation area) level, providing data availability to fill this gap. Here, we use hourly power operating locality level power outage, temperature, precipitation, wind speed, snowfall, lightning, urbanicity, and social vulnerability data across NYS to characterize the impact of extreme weather on power outage distributions and durations from 2017–2020. We also consider inequitable exposure by community vulnerability factors. We conduct analyses in three regions: NYC, non-NYC urban, and rural regions of NYS to assess (a) the lagged effect of severe weather on power outages, (b) the most prevalent combinations of severe weather types that contribute to outages, (c) the spatial distribution of the severe weather driven outages, and (d) disparities in severe weather-driven outages by community social vulnerability.

Methods

Study overview

In the present analysis, we use locality-level (n = 1,764) power outage, weather, urbanicity, and social vulnerability data from January 1, 2017-December 31, 2020 to assess the impact of extreme weather on power outage distributions and durations, while considering vulnerability factors.

Power outage ascertainment

We obtained information on customers without power in 30-minute increments within localities from the NYS Department of Public Service from 2017–2020 [23]. We excluded localities with $<$30 customers or $>$5% temporal missingness over the study period, resulting in 1,764 (94.6%) included localities. The dataset also included locality boundaries in a shapefile format and the number of customers served, and the electrical utilities operating in each locality. A power operating locality is the smallest level at which outage data is reported to the state and is comparable in size to zip code tabulation areas; the localities serve ~11,000 customers, on average. These customers include residential, commercial, and electrical meters. We aggregated the 30-minute data to the hourly level to match our weather metric data.

Weather metric ascertainment

We primarily sourced weather data from land-surface model estimates. We pulled data on average temperature, windspeed, and precipitation at the hourly-level from forcing data for Phase 2 of the North American Land Data Assimilation System (NLDAS-2) [24]. NLDAS-2 provides gridded estimates of each of these variables with ~14km^2 resolution. We obtained hourly snowfall data from the ERA5-Land reanalysis dataset, which is available hourly with ~11km^2 resolution [25]. We aggregated the gridded datasets to locality boundaries via areal weighting using Google Earth Engine [26]. We collected lightning strike data from the International Space Station Lightning Imaging Sensor, which records the time and location of lightning strikes, starting in March 2017 [27]. To match the spatial and temporal resolution of the other data, we calculated the hourly number of lightning strikes in each locality. Since lightning data was only available beginning March 2017, to preserve as much data as possible, we assumed no lightning strikes occurred during the first two months of 2017. Lightning strikes were most common from April to August (n = 1624 total strikes), and only 4 total strikes occurred in January and February 2018–2020 combined.

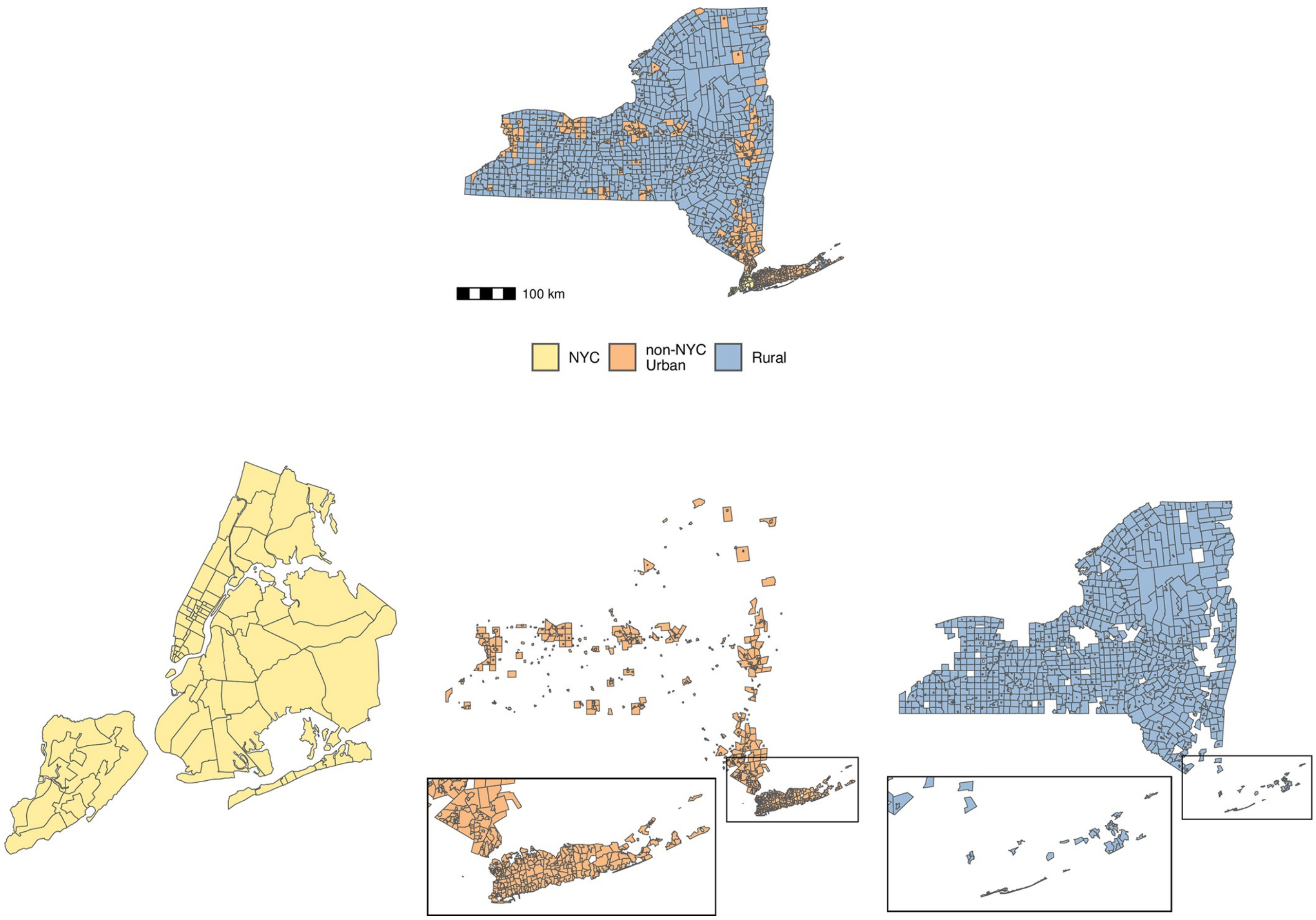

Fig 1. **The spatial boundaries of each power operating locality in NYC, non-NYC urban, and rural regions of NYS.** Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.

https://doi.org/10.1371/journal.pclm.0000364.g001

Urbanicity ascertainment

Because of unique population, outage, and weather profiles, we ran all analyses separately for NYC, non-NYC urban, and rural regions of NYS. To classify localities into their respective regions, we first used 2010 US Census on the percent of the total population classified as urban/rural at the block group. We interpolated this to the locality-level with areal weighting. When localities had >50% of inhabitants designated as rural, we assigned the locality a rural classification [28]. We distinguished between NYC and non-NYC urban, using the county indicators included in the power outage data. We assigned localities listed in the New York, Bronx, Kings, Queens, and Richmond counties as NYC. The final classification of each locality used in all further analysis is available in Fig 1 and S1 Fig.

The lagged effect of severe weather on power outages, by severe weather metric and by region

To assess the lagged and non-linear effects of weather on the proportion of customers without power in a locality, we used negative binomial generalized additive models, an extension of generalized linear models that allow for smoothed or nonlinear fits [29]. We selected the negative binomial fit after assessing regression diagnostics using the DHARMa package across a range of model types including Poisson, negative binomial, Tweedie, and zero-inflated Poisson [30]. We modelled weather using distributed lag nonlinear models (DLNMs), which simultaneously allow for the modelling of nonlinear exposure-outcome relationships and delayed events [31]. DLNMs are also advantageous because they provide constrained lag terms which account for high temporal autocorrelation, a feature of the hourly weather data. We adjusted for seasonal and temporal trends by including a natural spline term with 6 knots per year for the date [32]. We also included fixed effects for the utility that serves each locality to account for a lack of spatial independence. We used the Akaike information criterion to select the appropriate degrees of freedom for both the exposure and the lag out of a range of 2–5. We used the Moran's I to assess spatial autocorrelation in the final models (S15–S17 Figs) [33].

Outage, severe weather, and severe weather-driven outage classifications

For the remainder of our analyses, we conceptualized outages, severe weather events, and a severe weather-driven outage each as binary variables. We relied on the severe weather and power outage literature, our weather and outage data's distribution, and the results from our first objective, which assessed the lagged effect of severe weather on outages.

In previous literature, outages have been defined as hours where the proportion of customers without power exceeds the 90th percentile of the hourly proportion without power statewide [34, 35]. We adapted a similar definition for our analyses, but instead defined the 90th percentile separately for each region (NYC, urban non-NYC, and rural) to prevent the undercounting of outages in NYC, where the population in a locality was much larger than in rural regions. The 90th percentile of customers without power was 0.04%, 3.4%, and 15.2%, for NYC, non-NYC urban, and rural, respectively. As an example, for our binary outage metric, any hour where the percentage of customers without power exceeded 3.4% in a non-NYC urban power operating locality was classified as an outage.

We similarly used percentile classifications from our data distribution to determine the presence of a severe weather event. We hoped to identify pertinent thresholds in our first objective, but we observed the general pattern of outages increasing at the extreme of weather metric distributions rather than distinct thresholds. Thus, we used a statewide 97.5th percentile to define severe weather events. We chose to keep this metric statewide for interpretability. For most of the continuous metrics (precipitation, wind speed, snowfall) we identified the 97.5th percentile of each metric from 2017–2020, and then any hour above that threshold we defined as a severe-weather event. For temperature, the definition slightly deviated. To define extremely hot hours, we calculated the 97.5th percentile of temperatures during the during the hot months (May-Sept) and to define extremely cold hours, we calculated the 2.5th percentile during cold months (Oct-April). The presence of lighting was collapsed to a binary depending on whether a locality experienced any lightning strikes during that hour.

Finally, to create a severe weather-driven outage definition, we used the two previously described definitions and a lag component. Using the results from our first objective, it appeared that much of the effect of the extreme events was immediate (within 8–12 hours of exposure). Therefore, we decided to use 8 hours as our window of interest. Our final definition for a severe weather-driven outage was an outage that started either within the same hour of a severe weather event or within 8 hours following a severe weather event.

The most prevalent and hazardous combinations of severe weather types that contribute to outages

Once we defined outages and severe weather-driven outages, we used these definitions to achieve study objectives 2–4. We wanted to identify the severe weather events (or combination of severe weather events) that lead to the most significant power outages in frequency, duration, or proportion of customers impacted. To do so, we first calculated the frequency, average duration, and average proportion of customers impacted for each classification of severe weather driven outage (e.g., wind + precipitation-driven, wind-driven). We omitted snow-driven outages from this analysis to reduce the number of classes and redundancies between groups, as snow is part of the precipitation estimates.

We then calculated a severe/non-severe outage ratio for each severe weather combination. We calculated this using the following formula:

$$\frac{\left(\frac{\text{number of outages caused by with severe weather event } i}{\text{number of hours with severe weather event } i}\right)}{\left(\frac{\text{number of outages without } \textit{any} \text{ severe weather event}}{\text{number of hours without } \textit{any} \text{ severe weather event}}\right)}$$

where, for each severe weather combination, we divided the number of outages from a severe weather combination, by the number of hours with the severe weather combination. Then to standardize this across non-severe outages, we divided the numerator by the number of outages without any severe weather event divided by the hours without any severe weather events. A severe/non-severe ratio > 1 indicates that outages are more likely due to that severe weather combination, *i*, than times without any severe weather events. The ratios can then be compared across severe weather types to quantify which combinations are the most likely to cause outages.

The distribution of the severe weather driven outages across the state

With outages, severe weather driven outages, and pertinent combinations of severe weather types defined, we performed descriptive analyses by mapping the frequency, average number of customers without power, and the duration of outages during severe weather driven and non-severe weather driven outages for each region. We also calculated the percentage of outages that were due to severe weather events in each locality. Finally, we presented the frequency of severe weather driven outages by type. For this mapping and for subsequent analyses, to reduce the number of analyses, we present outages driven by each of the six weather metrics of interest (cold, heat, lightning, precipitation, snow, and wind). Thus, outages caused by both wind and precipitation would be counted in both the wind and precipitation panels of Fig 4.

Disparities in the frequency and duration of severe weather-driven outages

We then aimed to assess the association between social vulnerability and outage exposure.

Social vulnerability classification

We used the 2020 Social Vulnerability Index (SVI) created by the CDC/ATSDR to determine the social vulnerability of each power operating locality [36]. The CDC/ATSDR designed the index to identify communities that may need support during disasters like those driven by climate change. It incorporates 16 social factors from the 2016–2020 American Community Survey that capture several aspects of outage-related vulnerability (e.g., poverty, disability, housing type, age, English-language proficiency). The final index score ranges from 0–100 where higher values indicate increased social vulnerability. We downloaded the 2020 SVI at the census tract level, and used areal interpolation to determine the scores using to the power operating locality using a target-density weighting approach [37]. Finally, for each urbanicity region, we grouped each locality into their respective SVI quartile resulting in the final distribution displayed in S2 Fig.

Statistical analysis–the frequency and duration of severe weather-driven outages

To estimate disparities in the distribution of outages, we used targeted maximum likelihood estimation (TMLE) [38], a doubly robust maximum-likelihood–based approach. We estimate the average treatment effect of being in the highest quartile of SVI versus all others on risk of a severe weather-driven outage. We performed these analyses separately for each of the rural, non-NYC urban, and NYC regions. We implemented TMLE using the ltmle [39] and SuperLearner [40] packages in R. We ran three sets of sensitivity analyses. In the first, we stratified the analyses by year. In the second, we re-ran the analyses raising the thresholds for the number of severe-driven outages from n = 1+ to n = 3+ and then n = 5+. In the third, we included latitude and longitude to account for possible spatial confounding.

To understand disparities in the duration of outages, we present the duration of each outage type by SVI quartile along with results from Kruskal–Wallis tests [41]. All code for the conducted analyses are available on GitHub: https://github.com/nina-flores/nys_severe_weather_outages.

Results

From 2017–2020, we identified 40,646 electrical power outages, of which we linked 16,236 (39.9%) to severe weather. Non-severe weather-driven outages lasted 3.6 hours, on average, whereas outages due to severe weather events lasted anywhere from 3 to 17 hours, on average (Table 1).

The lagged effect of severe weather on power outages, by type and by region

Using DLNMs, we examined both nonlinear exposure-outcome relationships and delayed events, for each weather metric of interest. An example of the output from these analyses showing the lagged relationship between hourly temperatures and the proportion of customers without power for non-NYC urban localities is displayed in Fig 2. Here, we visualize the relative rate of customers without power as temperatures increase or decrease away from the median of 9.8˚C across 24 hours of lags. By focusing on the same hour of exposure, lag 0, we found that an increase in temperature to 30˚C in non-NYC urban localities leads to 3.8 (95% CI: 3.6–4.1) times the rate of customers without power, during that same hour of the temperature increase, compared to the median temperature. However, we observed a 5–15-hour lag between extreme cold temperatures and an increased rate of outages. We created a Shiny dashboard so that readers could view the 3D plots (Fig 2A) and 2D plots across any number of lags up to 24 (Fig 2B) for each of the weather metrics (precipitation, snowfall, temperature, and windspeed) and each of the regions of analysis (NYC, non-NYC urban, rural; https://oyb6ek-nina-flores.shinyapps.io/severe-weather-app/).

We found that the weather metrics most strongly associated with power outages varied by region: in NYC and non-NYC urban areas, precipitation led to the largest rate ratios whereas in rural NYS, extreme wind led to the largest rate ratios. However, no region had a clear threshold at which any of the weather metrics distinctly increased outages. Rather, there was a smooth trend that outages increased as each weather metric became more extreme.

Lagged effects differed by weather metric and region. For instance, in non-NYC urban areas, extremely hot temperatures (>30˚C) were most strongly associated with immediate increases in the rate of outages whereas extremely cold temperatures (<-10˚C) were most

Table 1. The frequency, average duration, and average customers out during severe weather driven outages, by weather types and by region.

		Overall			NYC			Non-NYC urban			Rural		
Number of causes	Cause(s)	Frequency n (%)	Duration in hours: mean (sd)	Proportion of customers without power: mean (sd)	Frequency n (%)	Duration in hours: mean (sd)	Proportion of customers without power: mean (sd)	Frequency n (%)	Duration in hours: mean (sd)	Proportion of customers without power: mean (sd)	Frequency n (%)	Duration in hours: mean (sd)	Proportion of customers without power: mean (sd)
single	no severe weather	24410 (60.1)	3.6 (7.2)	0.3 (0.3)	5071 (66.9)	4.2 (8.4)	0 (0)	10314 (57.6)	3.2 (7.1)	0.2 (0.2)	9025 (59.6)	3.7 (6.5)	0.5 (0.3)
	wind	6972 (17.2)	11.7 (27.6)	0.2 (0.2)	1035 (13.7)	8.7 (24.6)	0 (0)	3072 (17.1)	15.7 (35.9)	0.1 (0.2)	2865 (18.9)	8.6 (14.8)	0.3 (0.2)
	precipitation	3678 (9.0)	6 (13.2)	0.2 (0.2)	230 (3.0)	4.9 (5.2)	0 (0)	1698 (9.5)	6 (16.2)	0.1 (0.2)	1750 (11.5)	6.3 (10.4)	0.4 (0.2)
	heat	2540 (6.2)	4.7 (8.8)	0.1 (0.2)	947 (12.5)	5.5 (7.8)	0 (0)	1152 (6.4)	4.3 (9.4)	0.1 (0.1)	441 (2.9)	3.8 (8.9)	0.4 (0.2)
	cold	282 (0.7)	3.1 (3.8)	0.3 (0.3)	9 (0.1)	5.3 (3)	0 (0)	96 (0.5)	2.7 (2.2)	0.2 (0.2)	177 (1.2)	3.2 (4.5)	0.4 (0.3)
	lightning	29 (0.1)	5.8 (6.6)	0.3 (0.2)	2 (0.0)	6 (5.7)	0 (0)	6 (0.0)	11.5 (11.9)	0.1 (0.1)	21 (0.1)	4.1 (3.4)	0.3 (0.2)
multiple	precipitation + wind	1878 (4.6)	16.5 (30.3)	0.2 (0.2)	135 (1.8)	20.2 (46.5)	0 (0)	1091 (6.1)	18.5 (33.2)	0.1 (0.1)	652 (4.3)	12.5 (18.2)	0.3 (0.2)
	heat + precipitation	718 (1.8)	5.6 (7.2)	0.2 (0.2)	117 (1.5)	6.9 (6.4)	0 (0)	445 (2.5)	5.5 (7.6)	0.1 (0.1)	156 (1.0)	4.9 (6.2)	0.4 (0.2)
	cold + wind	63 (0.2)	4.3 (5.3)	0.1 (0.2)	24 (0.3)	5 (6.3)	0 (0)	21 (0.1)	3.3 (4.1)	0.1 (0.1)	18 (0.1)	4.5 (5.1)	0.4 (0.2)
	heat + wind	33 (0.1)	3.2 (3.9)	0.3 (0.2)	0 (0.0)	0 (0)	0 (0)	9 (0.1)	4.1 (6)	0.1 (0.1)	24 (0.2)	2.8 (2.9)	0.3 (0.2)
	lightning + precipitation	17 (0.0)	3.1 (2.2)	0.3 (0.3)	2 (0.0)	5 (2.8)	0 (0)	4 (0.0)	2.8 (1)	0 (0)	11 (0.1)	2.8 (2.4)	0.4 (0.2)
	heat + lightning + precipitation	10 (0.0)	4 (3.9)	0.2 (0.3)	2 (0.0)	10.5 (3.5)	0 (0)	4 (0.0)	2.2 (1)	0.1 (0)	4 (0.0)	2.5 (2.4)	0.4 (0.3)
	heat + precipitation + wind	9 (0.0)	3.7 (3.6)	0.4 (0.3)	0 (0.0)	0 (0)	0 (0)	3 (0.0)	3 (1)	0.1 (0.1)	6 (0.0)	4 (4.5)	0.6 (0.3)
	lightning + wind	4 (0.0)	3 (2.2)	0.3 (0.3)	0 (0.0)	0 (0)	0 (0)	3 (0.0)	3.7 (2.1)	0.1 (0.1)	1 (0.0)	1 (NA)	0.7 (NA)
	heat + lightning	3 (0.0)	3 (1)	0.1 (0.1)	1 (0.0)	2 (NA)	0 (NA)	0 (0.0)	0 (0)	0 (0)	2 (0.0)	3.5 (0.7)	0.2 (0)
	Total	40646 (100.0)			7575 (100.0)			17918 (100.0)			15153 (100.0)		

Each severe weather-driven outage type is defined as an outage that started either within the same hour of the severe weather event(s) or within 8 hours following the severe weather event(s). Boxes highlighted in orange have values above outages driven by causes other than severe weather (highlighted in purple). Boxes highlighted in blue have values below outages driven by causes other than severe weather (highlighted in purple).

https://doi.org/10.1371/journal.pclm.0000364.t001

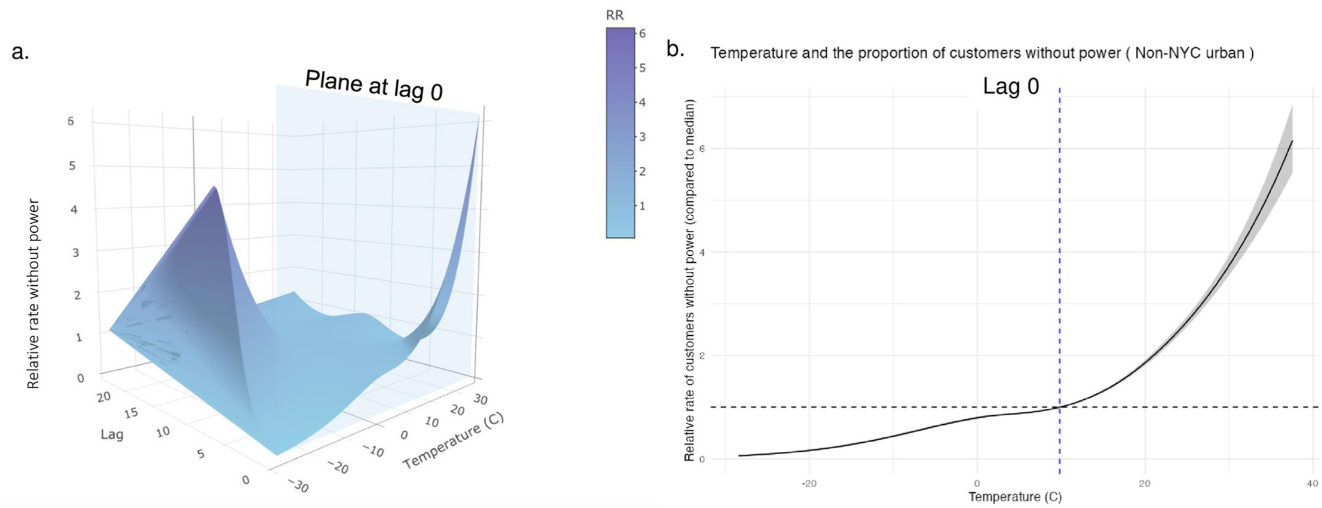

Fig 2. The lagged relationship of hourly temperature and the proportion of customers without power for non-NYC urban localities at all lags 0–24 (a), and at lag 0 (b). Panel b is constructed by slicing panel a where the lag = 0, as shown by the light blue plane at lag 0. All rates are relative to the overall median temperature of 9.8˚C, shown by the dotted blue vertical line (b). To view these figures for all other weather metrics (precipitation, snowfall, temperature, and windspeed) and regions of analysis (NYC, non-NYC urban, rural), please visit our shiny dashboard: https://oyb6ek-nina-flores.shinyapps.io/severe-weather-app/.

https://doi.org/10.1371/journal.pclm.0000364.g002

strongly associated with increases in the rate of outages after 6–8 lagged hours. However, in rural regions of NYS, the impacts of extremely hot and extremely cold temperatures were most observable at lag 0. Though there was heterogeneity in the lagged effects, we observed that the effect peaked across most weather metrics and regions after 8–12 lagged hours, which influenced our final definition of weather-driven outages.

The most prevalent and hazardous combinations of severe weather types that contribute to outages

We identified outages that exceeded the region (NYC, non-NYC urban, and rural) specific 90th percentile of customers without power and described their summary statistics (Table 1). By calculating the frequency of outages, their average duration, and the average proportion of customers without power during outages, by severe weather cause, we found that wind was the most frequent and the strongest single predictor of prolonged outages across all 3 regions (Table 1). Following wind, precipitation and heat alone also had consistently high frequency and durations across regions. Extreme cold alone had varying impacts across regions. For instance, in rural regions of NYS, outages driven by extreme cold were less likely to induce prolonged outages than non-severe weather conditions; however, in NYC, extreme cold conditions were more likely to cause prolonged outages than non-severe weather conditions.

When comparing multiple severe weather metrics simultaneously, we found that some combinations of multiple severe weather events led to longer or more widespread outages than single causes alone. The combination of extreme precipitation + wind led to the longest average duration for any severe weather type across all three regions, with an average duration of 20.2 hours in NYC, 18.5 hours in non-NYC urban, and 12.5 hours in rural NYS.

Using a severe/non-severe weather ratio to understand the impact of each weather metric on outages, we found that, though outages associated with lightning were relatively infrequent, they were the most likely single severe weather event to co-occur with outages across all 3 regions (Table 2). Following lightning, precipitation and wind also had consistently high

Table 2. The frequency and severe/non-severe weather ratios for each weather driven outage.

		Overall		NYC		non-NYC Urban		Rural	
Number of events	Severe weather event(s)	Frequency of outages of this combination	Ratio[1]	Frequency of outages of this combination	Ratio[1]	Frequency of outages of this combination	Ratio[1]	Frequency of outages of this combination	Ratio[1]
	no severe weather	24410	1.0	5071	1.0	10314	1.0	9025	1.0
single	lightning	29	105	2	106	6	117	21	141
	precipitation	3678	30	230	8.9	1698	32	1750	39
	wind	6972	11.5	1035	4.7	3072	11.2	2865	14.2
	heat	2540	9.4	947	5.2	1152	7.8	441	7.1
	cold	282	0.8	9	1.3	96	1.2	177	1.0
multiple	heat + lightning + precipitation	10	23819	2	-	4	-	4	14431
	lightning + precipitation	17	378	2	-	4	390.5	11	472
	lightning + wind	4	733	-	-	3	2245.1	1	361
	heat + precipitation	718	391	117	55.3	445	478.0	156	445
	precipitation + wind	1878	182	135	22.6	1091	186.0	652	276
	heat + lightning	3	101	1	53.2	-	-	2	180

[1]A severe/non-severe ratio > 1 indicates that outages are more likely due to that severe weather combination, *i*, than times without any severe weather events.

https://doi.org/10.1371/journal.pclm.0000364.t002

severe/non-severe weather ratios across regions. Extreme cold alone had varying impacts across regions. For instance, in rural regions of NYS, outages driven by extreme cold were less likely to induce outages than non-severe weather conditions, however, in NYC, extreme cold conditions were more likely to cause outages than non-severe weather conditions.

When comparing multiple severe weather metrics simultaneously, we found that, generally, the combination of multiple severe weather events had higher ratios than single events alone. Overall, the top 5 combinations driving outages of multiple types, heat + lightning + precipitation, lightning + precipitation, lightning + wind, heat + precipitation, and precipitation + wind, all had ratios greater than lightning's 105. Of note, heat + precipitation and precipitation + wind were both frequent (caused 718 and 1,878 outages, respectively) and had high severe/non-severe weather ratios.

Across NYS, 39.9% of all outages co-occurred with severe weather (Table 1). However, there was heterogeneity in this percentage across regions and localities. Severe weather contributed to over 50%, 85%, and 87% of all outages in some NYC, non-NYC urban, and rural localities, respectively. Across all 3 regions, generally, severe weather-driven outages impacted larger percentages of electrical customers and had longer durations than non-severe weather-driven outages (S3–S6 Figs and Table 2). In maps of the frequency of severe weather-driven outages overall and by weather metric, we found that certain localities were vulnerable to outages across all severe weather metrics. In NYC, localities in Queens, the Bronx, and Staten Island experienced the most severe weather-driven outages, with localities in Queens experiencing outages driven by each weather metric (cold, heat, lightning, precipitation, snow, and wind; Fig 3). In non-NYC urban regions, the most frequent severe weather outages occurred on Long Island and in the Hudson Valley and in rural regions, the most frequent severe weather outages occurred in North and Central NYS (S7 and S8 Figs).

In analyses assessing whether differences in the distribution of outages were due to social vulnerability, we found different effects across urbanicity (Fig 4). We estimated that in NYC, had all regions been in the 4th quartile of SVI the number of heat-, precipitation-, and wind-

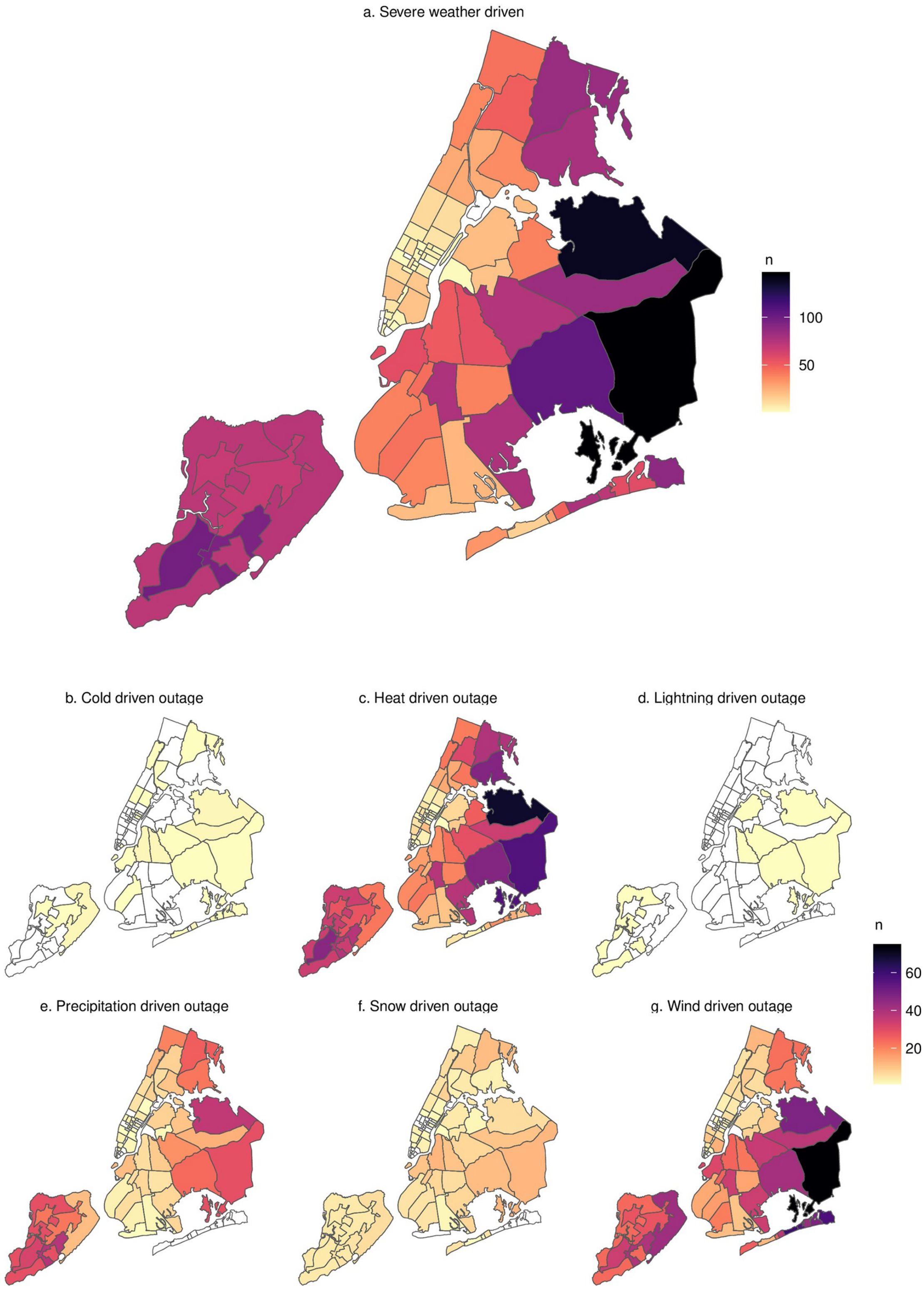

Fig 3. The frequency of (a) any severe weather driven outage and the frequency of outages co-occurring with extreme (b) cold, (c), heat, (d) lightning, (e) precipitation, (f) snow, and (g) wind in NYC, from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.

https://doi.org/10.1371/journal.pclm.0000364.g003

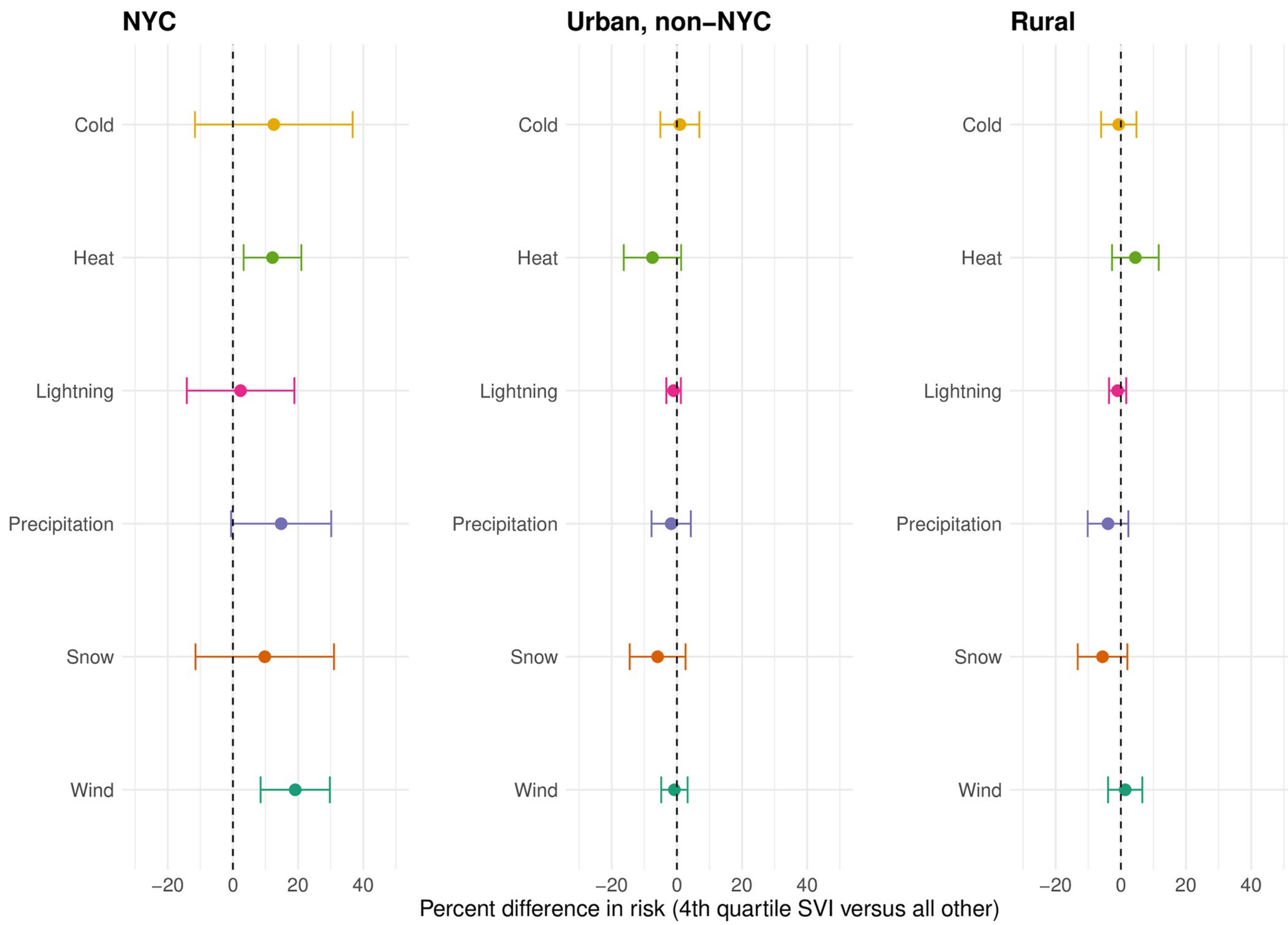

Fig 4. The percent difference in the average treatment effect comparing the highest quartile of SVI (most vulnerable) to all others, presented for each outage cause and by urbanicity. The percentages can be interpreted as the percent difference in the probability of an outage of each severe weather type had all localities been in the highest quartile of SVI (most vulnerable) versus if all localities had been in quartiles 1–3, presented for each outage cause and by urbanicity.

https://doi.org/10.1371/journal.pclm.0000364.g004

driven outages would have been 12.1% (3.3%, 21.0%), 14.8% (-0.5%, 30.2%), and 19.1% (8.5%, 29.8%) higher, respectively, versus if all localities had been in quartiles 1–3. We estimated that in non-NYC urban NYS, had all regions been in the 4th quartile of SVI the number of heat-driven outages would have been 7.5% lower (-16.3%, 1.3%), versus if all localities had been in quartiles 1–3. Finally, in rural NYS, we estimated that if all regions had been in the 4th quartile of SVI the number of snow-driven outages would have been 5.6% lower (-13.2%, 2.0%), versus if all localities had been in quartiles 1–3. Otherwise, SVI did not seem to have an impact on outage frequency for non-NYC urban and rural localities. These results were consistent with a sensitivity analysis that used higher counts of severe weather outages (n = 3+ and 5+, rather than n = 1+) as the outcome (S9 Fig). When stratifying analyses by year, in NYC we found significantly positive associations between SVI and snow-driven outages for the year 2018–2019 as well (S10 Fig). When adding latitude and longitude to the models to account for possible spatial confounding, most estimates remained the same. However, in NYC there was no longer a relationship between vulnerability and precipitation-driven outages (S11 Fig).

The duration of some outage types was also longer in regions with higher SVI; for example, outages driven by wind and precipitation lasted the longest in regions in the 4th quartile of SVI

(SVI Q1 = 15.0, SVI Q2 = 17.2, SVI Q3 = 15.8, and SVI Q4 = 18.0 hours, S1 and S2 Tables). However, this also varies by region (S12–S14 Figs). In NYC, outages with the longest durations in high vulnerability regions co-occurred with precipitation whereas in rural regions, these co-occurred with precipitation and snow.

Discussion

In this analysis, we assessed severe weather-driven outages in NYS from 2017–2020 by region and social vulnerability. We found that the frequency, duration, and magnitude of outages depend on a combination of severe weather type, urbanicity, and vulnerability status. In NYC, severe weather driven outage were more common and lasted longer in marginalized communities. In rural regions, outages were no more common in socially vulnerable communities but when they occurred, lasted longer for socially vulnerable communities.

This paper is among the first to consider differences in severe weather-driven outages across urbanicity. This stratification is important because differences in housing stock (e.g., size, attached/detached), grid infrastructure (e.g., presence of overhead/buried distribution lines, sprawl), population size/density, and behaviors surrounding energy often vary by urbanicity [42]. Furthermore, region-specific analyses are important in the context of climate change because climate change drives unexpected weather event occurrences and magnitudes that the grid may be ill-equipped to handle. Severe weather intensity may be region and urbanicity specific due to the urban heat island effect, proximity to water, and tree canopy. The NYC, non-NYC urban, and rural stratification provided nuance to our analyses of outage prevalence and disparities.

Our definition of severe weather-driven outages allows us to more precisely understand the relationship between weather and outages. Including a temporal component of severe weather-driven outages (i.e., considering lagged effects of weather to determine severe-weather related outage) improves upon previous definitions of severe weather-driven outages that use the co-occurrence of outages on the same day to define outages [35]. The previous definition did not (a) account for outages occurring earlier in the day than the extreme event or (b) incorporate lagged effects of outages on the preceding day–two limitations our definition overcomes. Our definition could be used in future papers or further adapted to more accurately define outages or other adverse events caused by severe weather.

By investigating the most prevalent and hazardous combinations of severe weather types that contribute to outages, we found that extreme heat/precipitation and extreme precipitation/wind were the most likely to precede outages while extreme precipitation/wind and extreme wind alone led to the longest outage durations. This was largely consistent across the three regions studied and with a national assessment of severe weather and power outages, which found that 8+ hour outages were the most likely to occur on county-days with heavy precipitation/cyclone /heat and heavy precipitation/cyclone [35]. Our analyses revealed that, though the likelihood of outages due to these events may be similar across urbanicity, the restoration times differed. The average duration of outages due to extreme precipitation/wind in rural regions was 12.5 hours compared to 18.5 hours in non-NYC urban and 20.2 hours in NYC regions, respectively. Such information is critical for utilities, policymakers, and electricity users preparing for outages in a changing climate.

By investigating disparities in the frequency and duration of severe weather-driven outages, we add to a growing literature identifying disparities in power outage experiences, though we highlight that this varies across urbanicity. Previous analyses of major severe weather-driven outages demonstrated evidence of disparities, across a range of locations. Outages during the 2021 Texas Power Crisis were more widespread and longer in counties with a higher percentage of Hispanic residents [20]. Outages after Hurricane Irma were longer in regions with more Hispanic residents, regions with more residents with disabilities, and rural regions [21]. Outages in New York City resulting from Tropical Storm Isaias were longer in regions that were lower income and/or had higher percentages of non-White residents [22]. Previous work posits that increased outage exposure in vulnerable communities may be the result of historical and current discriminatory practices. Practices such as redlining and zoning have had longstanding impacts, including (1) underinvestment in marginalized communities and (2) the placement of marginalized communities in disaster-prone regions–both of which may make these communities more likely to experience outages. During outage events, many electric utilities prioritize power restoration in regions with community assets, such as mass transit, hospitals, police and fire stations, and sewage and water stations. Regions with these assets were outlined as a priority for Con Edison in NYS following Tropical Storm Ida in September of 2021 [43]. By tying power restoration preferences to community assets, these guidelines can lead to inequitable outage distributions and durations for underfunded and under-resourced communities [16].

We found evidence of disparities in outages by community social vulnerability, with variation by region and severe weather event. In NYC, we identified that heat-, precipitation-, and wind-driven outages disproportionately impacted vulnerable communities. We also found that in NYC, on average, the duration of precipitation-driven outages was highest in localities with the highest social vulnerability. In rural NYS, on average, the duration of precipitation- and snow-driven outages were higher in localities with greater social vulnerability. Given the centrality of electrical energy for daily life in the US, an imbalance in electrical disruptions (in distribution, duration, or health impact) is inherently an environmental justice and climate justice issue. Furthermore, the energy transition will result in greater reliance on electricity for heating, cooking, and transit, making electrical disruptions even more impactful [12]. We add that plans to achieve grid reliability may look different across urbanicity. For example, NYC may prioritize improvements that increase reliability during extreme precipitation, as extreme precipitation-driven outages were both more frequent and longer in vulnerable regions. While reliability remains a concern, it is important to ensure that urban dwellers have safe backup power options. Diesel generators, for example, are commonly used as backup power sources but "emit pollutants, are prone to failure, can be difficult to operate and refuel", and have been linked to spikes in carbon monoxide poisonings observed with natural disasters [44]. Cleaner backup power sources are becoming available (e.g., solar + storage [44]) but may require further work to fully incorporate urban and low-income communities. Residents in multiple unit housing face more challenges in accessing backup power options than people living in single family homes, a housing typology more common in suburban and rural areas. Such that even if people living in low density housing setting are experiencing more frequent outages, they are likely equipped with whole house generators that reduce the likelihood of a full interruption in contrast to apartment dwellers. Furthermore, any out-of-pocket expenses required for backup options may be inhibitive for low-income renters. Thus, developing programs that can provide these options for renters free of fees, as was done in a pilot program providing Powerwall battery systems to customers in Vermont, could be one way to equitably move toward resilient power [44]. Based on our results, rural NYS may instead prioritize addressing the longer durations of outages in vulnerable communities during extreme snow or precipitation. This could look like prioritizing power restoration in regions with higher concentrations of low-income and/or medically vulnerable individuals first.

In the 2011–2021 decade, the United States experienced a 78% increase in weather-related power outages, compared to the previous decade [45]. Addressing power outages, in the face of climate change and the energy transition is a public health issue [45]. Power outages can directly impact health through a variety of mechanisms. These include carbon monoxide poisoning, a common consequence of using generators to cope with outages [46, 47], or the exacerbation of underlying cardiovascular, respiratory, renal, and mental health diseases due to sudden shifts in temperature, air filtration, stress, physical activity (e.g., through using the stairs when an elevator in not powered), or status of electricity-dependent medical devices [13, 44]. As such, increasing electrical reliability, equitably, will be a key part of a just energy transition and climate justice.

Our analysis had limitations. First, though the meteorological data was the most temporally resolved available, it is still hourly averages (or totals). Therefore, results from our first objective cannot be interpreted as the exact values at which power outages occur, but rather show that generally, power outages increase as each of the meteorological variables become more extreme. Second, we added nuance to our analyses by focusing on urbanicity differences. However, the urbanicity classifications were still quite coarse. Refining these classifications by incorporating information on population density or region (e.g., rural-central NYS) may provide deeper insights. Third, our choice to use 8 hours of lags rather than a larger value (e.g., 12, 24) may undercount the number of outages that had a severe weather antecedent. We chose 8 hours to be more conservative as many of the increased rates of outages due to severe weather peaked near 8 hours. Fourth, we used the CDC's social vulnerability index as a metric of social vulnerability because it was designed to identify communities that may need support during disasters like those driven by climate change and it incorporates social variables that capture several aspects of outage-related vulnerability like poverty, disability, housing type, age, English-language proficiency. Though this index includes a comprehensive list of outage-relevant variables, important variables may still be omitted. For example, when creating plans for disaster or grid management, one may directly want to know the number of individuals using electricity-dependent medical devices. Though this may be partially captured by disability or correlate with poverty and age, the use of the index alone may not fully identify regions or households with more severe electricity vulnerabilities. Fifth, it is important to note that a power outage does not equate to powerlessness for everyone because it is customary in places where outages are more frequent to have backup generators, and many houses that are equipped with them have an automatic switch over in the context of an outage. For urban dwellers the lack of backup power options may indeed render them without power for the duration of the outage [48]. This is especially problematic for socially and medically vulnerable groups, but we cannot decipher whether outages herein were directly related to powerlessness. Finally, our results may not be generalizable outside of NYS. Instead, our results highlight the importance of considering regional and social differences to inform grid improvements. Such information can promote climate justice in the modernization of the US electrical grid.

Conclusion

The US power grid is proven to be highly reliable in general; however, the resilient and reliable grid operation is increasingly challenged by severe weather events–events that are increasing in frequency and magnitude due to climate change. Considering the adverse health impacts of power outages and the increasing reliance on electricity, addressing severe weather-driven electrical outages is critical for population health and environmental and climate justice. Our NYS analysis provides a definition of severe weather-driven outages that could be used to document the impacts of power outages further, especially those co-occurring with severe weather. Here, we document that, regardless of region, extreme heat/precipitation and extreme wind/precipitation were the most likely to precede outages from 2017–2020. We also provided region-specific information, highlighting that outage lasted the longest for vulnerable, rural communities following snow or precipitation. Thus, we highlight the importance of considering regional, social, and economic characteristics to inform equitable grid management and improvements.

Supporting information

S1 Fig. The spatial boundaries of each power operating locality in NYC, non-NYC urban, and rural regions of New York State with a map of New York state's location in the contiguous United States for reference. Map of the contiguous United States was obtained from the US census: https://www.census.gov/. Locality map republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S2 Fig. Locality assignment to quartiles of the CDC's social vulnerability index, by region. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S3 Fig. The percentage of all outages that were caused by severe weather in NYC, non-NYC urban, and rural NYS from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S4 Fig. Comparison of the frequency, proportion out, and duration of power outages for non-severe weather driven (left) and severe weather driven outages in NYC from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S5 Fig. Comparison of the frequency, proportion out, and duration of power outages for non-severe weather driven (left) and severe weather driven outages in non-NYC urban NYS from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S6 Fig. Comparison of the frequency, proportion out, and duration of power outages for non-severe weather driven (left) and severe weather driven outages in rural NYS from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S7 Fig. The frequency of (a) any severe weather driven outage and the frequency of outages driven by extreme (b) cold, (c), heat, (d) lightning, (e) precipitation, (f) snow, and (g) wind in non-NYC urban NYS, from 2017–2020. Republished from The New York State Department of Public Service under a CC BY license, with permission from The New York State Department of Public Service original copyright 2020.
(PDF)

S8 Fig. The frequency of (a) any severe weather driven outage and the frequency of outages driven by extreme (b) cold, (c), heat, (d) lightning, (e) precipitation, (f) snow, and (g) wind in rural NYS, from 2017–2020.
(PDF)

S9 Fig. The percent difference in the average treatment effect comparing the highest quartile of SVI (most vulnerable) to all others, presented for each outage cause and by urbanicity. The percentages can be interpreted as the percent difference in the probability of 1 + outage of each severe weather type had all localities been in the highest quartile of SVI (most vulnerable) versus if all localities had been in quartiles 1–3, presented for each outage cause and by urbanicity. We also present the results for 3+ and 5+ outages of each severe weather type.
(PDF)

S10 Fig. The percent difference in the average treatment effect comparing the highest quartile of SVI (most vulnerable) to all others, presented for each outage cause and by urbanicity. The percentages can be interpreted as the percent difference in the probability of 1 + outage of each severe weather type had all localities been in the highest quartile of SVI (most vulnerable) versus if all localities had been in quartiles 1–3, presented for each outage cause and by urbanicity. We also present the results for by year.
(PDF)

S11 Fig. The percent difference in the average treatment effect comparing the highest quartile of SVI (most vulnerable) to all others, presented for each outage cause and by urbanicity. These models included latitude and longitude variables. The percentages can be interpreted as the percent difference in the probability of 1+ outage of each severe weather type had all localities been in the highest quartile of SVI (most vulnerable) versus if all localities had been in quartiles 1–3, presented for each outage cause and by urbanicity.
(PDF)

S12 Fig. Violin plots of the duration of outages caused by each weather metric from 2017–2020 in NYC.
(PDF)

S13 Fig. Violin plots of the duration of outages caused by each weather metric from 2017–2020 in non-NYC urban NYS.
(PDF)

S14 Fig. Violin plots of the duration of outages caused by each weather metric from 2017–2020 in rural NYS.
(PDF)

S15 Fig. Map of the residuals for NYC. The Moran's I was: -.05 with a p-value of .07.
(PDF)

S16 Fig. Map of the residuals for non-NYC, urban NYS. The Moran's I was: < .001 with a p-value of .87.
(PDF)

S17 Fig. Map of the residuals for rural NYS. The Moran's I was: .003 with a p-value of .18.
(PDF)

S1 Table. The frequency, average duration, and average customers out during severe weather driven outages, by type and by SVI quartile.
(PDF)

S2 Table. The frequency and severe/non-severe weather ratios for each weather driven outage by SVI quartile.
(PDF)

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