



# The independent and synergistic impacts of power outages and floods on hospital admissions for multiple diseases



Xinlei Deng<sup>a</sup>, Samantha Friedman<sup>b</sup>, Ian Ryan<sup>a</sup>, Wangjian Zhang<sup>c</sup>, Guanghui Dong<sup>c</sup>, Havidan Rodriguez<sup>d</sup>, Fangqun Yu<sup>e</sup>, Wenzhong Huang<sup>e</sup>, Arshad Nair<sup>f</sup>, Gan Luo<sup>f</sup>, Shao Lin<sup>a,g,\*</sup>

<sup>a</sup> Department of Environmental Health Sciences, School of Public Health, University at Albany, State University of New York, USA

<sup>b</sup> Department of Sociology, University at Albany, State University of New York, USA

<sup>c</sup> School of Public Health, Sun Yat-sen University, Guangzhou, China

<sup>d</sup> University at Albany, State University of New York, USA

<sup>e</sup> School of Public Health and Preventive Medicine, Monash University, Australia

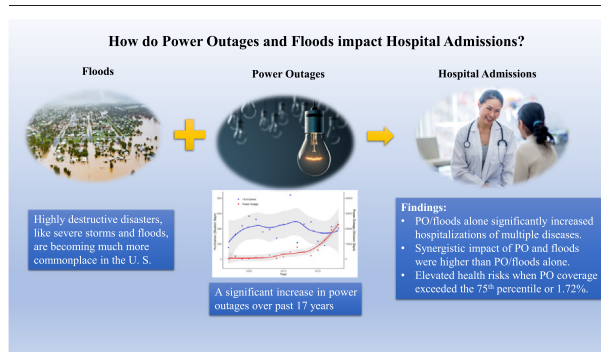
<sup>f</sup> Atmospheric Sciences Research Center, University at Albany, State University of New York, USA

<sup>g</sup> Department of Epidemiology and Biostatistics, School of Public Health, University at Albany, State University of New York, USA

## HIGHLIGHTS

- Power outage (PO) events significantly increased over time.
- PO/floods alone significantly increased hospitalizations of multiple diseases.
- Synergistic impact of PO and floods were higher than PO/floods alone.
- Elevated health risks when PO coverage exceeded the 75th percentile or 1.72%.

## GRAPHICAL ABSTRACT



## ARTICLE INFO

### Article history:

Received 22 December 2021

Received in revised form 24 February 2022

Accepted 28 February 2022

Available online 5 March 2022

Editor: Jay Gan

### Keywords:

Power outage

Floods

Cardiovascular diseases

Chronic respiratory diseases

Respiratory infections

Food-/water-borne diseases

## ABSTRACT

Highly destructive disasters such as floods and power outages (PO) are becoming more commonplace in the U.S. Few studies examine the effects of floods and PO on health, and no studies examine the synergistic effects of PO and floods, which are increasingly co-occurring events. We examined the independent and synergistic impacts of PO and floods on cardiovascular diseases, chronic respiratory diseases, respiratory infections, and food-/water-borne diseases (FWBD) in New York State (NYS) from 2002 to 2018. We obtained hospitalization data from the NYS discharge database, PO data from the NYS Department of Public Service, and floods events from NOAA. Distributed lag nonlinear models were used to evaluate the PO/floods-health association while controlling for time-varying confounders. We identified significant increased health risks associated with both the independent effects from PO and floods, and their synergistic effects. Generally, the Rate Ratios (RRs) for the co-occurrence of PO and floods were the highest, followed by PO alone, and then floods alone, especially when PO coverage is >75th percentile of its distribution (1.72% PO coverage). For PO and floods combined, immediate effects (lag 0) were observed for chronic respiratory diseases (RR:1.58, 95% CI: 1.24, 2.00) and FWBD (RR:3.02, 95% CI: 1.60, 5.69), but delayed effects were found for cardiovascular diseases (lag 3, RR:1.13, 95% CI: 1.03, 1.24) and respiratory infections (lag 6, RR:1.85, 95% CI: 1.35, 2.53). The risk association was slightly stronger among females, whites, older adults, and uninsured people but not statistically significant. Improving power system resiliency could be a very effective way to alleviate the burden on hospitals during co-occurring floods.

\* Corresponding author at: Department of Environmental Health Sciences, School of Public Health, University at Albany, State University of New York, USA.

E-mail address: [slin@albany.edu](mailto:slin@albany.edu) (S. Lin).

We conclude that PO and floods have independently and jointly led to increased hospitalization for multiple diseases, and more research is needed to confirm our findings.

## 1. Introduction

Highly destructive disasters, like severe storms and floods, are becoming much more commonplace in the U. S. (Smith, 2010–2019; NOAA, 2020). Since 1980, the U.S. has experienced 308 disasters from natural hazards that have resulted in damages of at least \$1 billion (NOAA, 2020). The frequency of these “billion-dollar” disasters is increasing – between 1980 and 2020, the average number of such disasters was 7.1 per year; however, since 2016, the average number of these significant events increased to 16.2 per year (NOAA, 2020). In 2020, there were 22 such events, marking the record for the single year with the most billion-dollar disasters (NOAA, 2020).

Power outages (PO) are also increasing in prevalence in the U.S. (Kenward and Raja, 2014; Chakalian et al., 2019). Since 2003, when stricter reporting requirements were put in place, the number of PO increased about fourfold, from about 60 outages in 2003 to nearly 240 outages in 2018 (Kenward and Raja, 2014; Chakalian et al., 2019). The average duration of PO is quite long, with estimates varying from an average of 49 min to as long as 4 h (U.S. Energy Information Administration (US EIA), 2018; Chrobak, 2020; American Society of Civil Engineers, 2017). Research has shown that windstorms are not the exclusive determinant of POs; rain and thunderstorms are significantly associated with these outages (Tonn et al., 2016; Mukherjee et al., 2018).

Linking PO to extreme weather events, such as floods, is critical not only because research demonstrates their connectedness but also because of their health implications. PO have been shown to increase the risk of hospitalizations, medical costs, mortality, and the number of comorbidities that are more commonly found in cardiovascular diseases (CVDs), chronic respiratory diseases (asthma and COPD), respiratory infections, and food-/water-borne diseases (FWBD) (Sheridan et al., 2021; Lin et al., 2021; S L, 2016; S L, 2011; Zhang et al., 2020; Anderson and Bell, 2012; Rocque et al., 2021; Musacchio et al., 2021). Extreme weather events, which include floods, cyclones, and hurricanes, have consistently been associated with health outcomes including mortality, anxiety or depression, and FWBD (Rocque et al., 2021; Musacchio et al., 2021; Andrade et al., 2018). In addition, Musacchio et al. (2021) and Andrade et al. (2018) reported an association between floods and waterborne infections or enteric diseases via groundwater contamination (Musacchio et al., 2021; Andrade et al., 2018). Quist et al. found acute gastrointestinal illness related to floods caused by hurricanes, while Christenson et al. reported severe community-acquired pneumonia and sepsis were associated with floods in Puerto Rico (Quist et al., 2022; Christenson et al., 2003).

Although the exact biological mechanisms of PO/floods affecting health are unknown, PO could be an immediate risk factor for COPD, asthma, or certain CVD exacerbations due to the interruptions in the oxygen supply and in the use of medication nebulizers and mechanical ventilation (Zhang et al., 2020). In addition, drinking water contamination, sewage overflow, and food spoilage during floods with PO could also explain the quick onset of food poisoning for FWBD and the delayed treatment of respiratory infections (Lane et al., 2013). Disaster-related psychosocial and post-traumatic stress could also trigger hypertension and ischemic heart disease, which was found among the Hurricane Katrina survivors (D E, 2013).

However, to our knowledge, there are no studies explicitly examining the joint effects of PO and floods, which are increasingly co-occurring events. It is likely that the synergistic impact of floods and PO could have a more substantial impact on health than examining each factor separately. In addition, nearly all prior studies evaluated a single, large-scale flood or one PO event (S L, 2011; Anderson and Bell, 2012; J B, 2008; JS P, 2010; SN J, 2009; Kessler et al., 2008; Mab et al., 2019). Previous studies have very limited sample sizes. Finally, substantial exposure misclassification regarding PO locations, the number of PO events, and PO coverage was

reported in previous studies because of the limitation and availability of PO data (Anderson and Bell, 2012; Casey et al., 2020; Li et al., 2020; KK J-A, 2014; Klein et al., 2007).

This study built upon and expanded the existing literature by examining the joint and independent effects of PO and floods, over time from 2002 to 2018, on hospitalizations for four major biologically relevant diseases, including CVDs, chronic respiratory diseases, respiratory infections, and FWBDs in New York State (NYS) by using unique PO data from NYS Department of Public Service covering all of NYS. Furthermore, we also identified the intensity of PO, compared the risk magnitudes among multiple diseases, described the lag effects, and demonstrated the different exposure-health associations by sociodemographic characteristics.

## 2. Material and methods

### 2.1. Health data and definition

Hospital admissions from NYS residents were obtained from the NYS Department of Health (NYSDOH) Statewide Planning and Research Cooperative System (SPARCS). Over 95% of hospitals in NYS were covered by the SPARCS database. Also, individual demographics and medical information including gender, age, race, ethnicity, health insurance, address, date of admission, principal diagnosis, and up to 24 comorbidities were available in the SPARCS database.

We obtained hospital admissions from 2002 to 2018 with a principal diagnosis of CVD, chronic respiratory diseases, respiratory infections, and FWBD with the following ICD-10 and ICD-9 codes.

- CVD: ICD-9: 393–396, 401–414, 427–428, 430–434, 436–438; ICD-10: I05–I08, I10–I25, I42, I47–I49, I50–I51, I60–I69
- Chronic respiratory diseases: ICD-9: 490–496; ICD-10: J40–J47
- Respiratory infections: ICD-9: 481, 482, 485–488; ICD-10: A48.1, J09–J11, J13–J18
- FWBD: ICD-9: 003–009; ICD-10: A00–A09

Each hospital admission was geocoded and assigned to one of the 1742 operating divisions of the electricity network defined by the NYS Department of Public Service. The health outcome was the sum of the daily number of hospital admissions for each disease at the operating division level. The comparison of other critical care indicators including length of stay and total hospital costs was conducted at the individual level. This study was approved by the Institutional Review Board at the University at Albany, State University of New York (approval number 17 × 189).

### 2.2. Exposure data and definition

#### 2.2.1. Flood data and definitions

We obtained the event data of floods from the Storm Events Database maintained by the National Weather Service of the National Oceanic and Atmospheric Administration (NOAA). This database (<https://www.ncdc.noaa.gov/stormevents/>) documented the occurrence of storms and other significant weather phenomena having sufficient intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce; rare, unusual, weather phenomena that generate media attention; and other significant meteorological events.

The event data contained the dates of events, locations, and the types of different weather events including floods (flash floods, floods, coastal floods, and lakeshore floods), and other weather events (e.g., snow-related events, thunderstorms, wind-related events, cold-related events, winter storms, and other events). These data categorize hurricanes as part of the flood group. We defined the event impact area/buffer by using the coordinates as the centers and the average distances from the reports as

the diameters. We then assigned each weather event to the corresponding power-operating division. We also conducted a sensitivity analysis by using only the coordinates (see eTable 1 in Appendix).

## 2.2.2. PO data and definitions

We obtained PO data (2002–2018) from the NYS Department of Public Service, including the total number of customers in each power operating division, the dates of PO, and the numbers of customers affected by PO. We estimated the coverage of PO by dividing the number of customers affected over the total and then defined the PO occurrence (Yes/No) as the PO coverage exceeding the 75th percentile of the distribution of PO coverage (1.72%) among all operating divisions and dates with PO. This definition of PO occurrence was based on previous studies (Sheridan et al., 2021; Lin et al., 2021; Zhang et al., 2020). Overall, health data, event data, and PO data were linked at the power operating division level.

## 2.2.3. Statistical analysis and confounders

In this study, we conducted a large time series design from 2002 to 2018 at the power operating division level, and the distributed lag nonlinear models (DLNM) (Gasparrini, 2011) were used to assess the potential association of floods and PO among four diseases. For each operating division, we conducted a DLNM model to compare the health outcomes during the three exposure periods (i.e., days with both floods and PO; days with floods only, and days with PO only) to the control days (i.e., neither of floods nor PO). The flooding and PO variables were combined as one variable with 4 categories: i.e., both floods and PO occurrence (1), floods only (2), PO only (3), and no-floods and no-PO (4, as the reference). For days with other weather events, if there were no floods or PO, we considered these days as the control days. Alternatively, the exposure-health associations were evaluated within the same division during different periods. For each division, confounders (Sheridan et al., 2021; Zhang et al., 2020) including air pollution concentrations ( $PM_{2.5}$ ,  $O_3$ ), various time-varying variables (including day of the week, holidays, season), temperature, and relative humidity were controlled in the model.

We specified our models as:

$\text{Log}(\text{cases}) \sim \text{cb}(\text{PO\&floods}) + \text{day of week} + \text{holiday} + \text{PM}_{25} + \text{O}_3 + \text{ns}(\text{time}) + \text{ns}(\text{day of the year}) + \text{ns}(\text{temperature}) + \text{ns}(\text{relative humidity})$

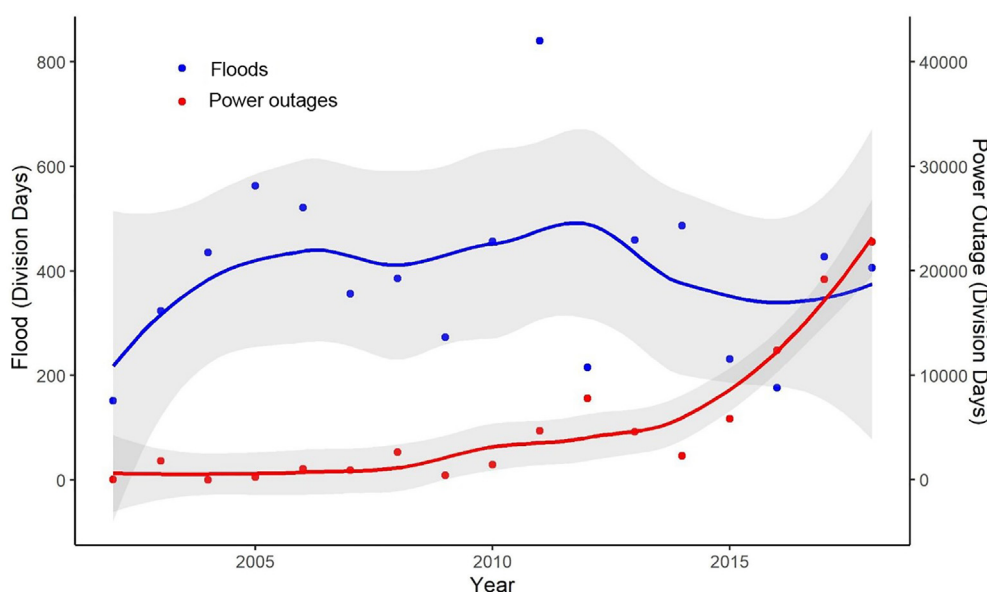
Where a case was the daily number of admissions, it followed a quasi-Poisson distribution to avoid overdispersion;  $\text{cb}(\text{PO\&floods})$  was the specific

cross-basis for the categorical variable regarding the day of PO/floods, with 3 degrees of freedom (df) for 0–6 lag days (individual) in the DLNM model;  $\text{ns}(\text{time})$  and  $\text{ns}(\text{day of the year})$  were splines with 4 df to control for the long-term trend of the time series of cases and potential seasonal effects;  $\text{ns}(\text{temperature})$  and  $\text{ns}(\text{humidity})$  were splines with 3 df to fit the confounding effects of temperature and humidity. The dfs were selected based on our previous studies (Sheridan et al., 2021; Lin et al., 2021; Zhang et al., 2020). The number of lag days was chosen based on our previous publications relating various health outcomes with other natural disasters, including winter storms and windstorms in NYS (Sheridan et al., 2021; Lin et al., 2021). Furthermore, the estimations were pooled at the operating division level to create an overall rate ratio (RR) across the state with a univariate fixed-effect meta-analysis. This was conducted with the `rma()` function in the R package “metafor” (CRAN - Package metafor. Accessed February 21, 2022).

To evaluate clinical burden in addition to morbidity, such as the economic costs for individuals and society, work or school days lost, and the severity of the diseases, we evaluated other critical care indicators such as cost of visit and length of stay at the individual level. Specifically, we compared the cases with four studied diseases during the three exposure periods (PO only, floods only, and both PO and flood co-occurrence) to cases at a control period when there was no flooding and no PO (see eTable 2 in Appendix), using the mean comparison based on the simulation method as described in our previous study (Zhang et al., 2020). Because the study period included Hurricane Sandy, which was defined as occurring between 10/22/2012–11/02/2012 by the Federal Emergency Management Agency, we conducted a sensitivity analysis from 2002 to 2011 that excluded the impact of this influential hurricane. Because Hurricane Sandy may cause both short-term and long-term health effects, we removed all cases after 2012 to control for the confounding effect from this hurricane. We present this sensitivity analysis in the Appendix (eTable 3). All analyses were conducted in R 4.1.0.

## 3. Results

Fig. 1 shows the annual variation of floods and PO in NYS. While the number of flood division days did not increase dramatically, the total number of PO division days has increased significantly since 2008 and has been accelerating since 2014 (Fig. 1, division days were defined as how many days of floods or PO were in a specific division). Among all extreme



**Fig. 1.** The annual variation of the number of division days for floods and PO in NYS, 2002–2018. Division days were defined as how many days of Floods or PO in a specific division.

weather events in NYS, floods constituted 12.5% of extreme weather events (data not shown). Fig. 2 shows the spatial distribution of floods and PO events at the power-operating division level in NYS, which differ significantly. By aggregating the data to the county level, we find that the top ten counties according to the total number of flood division days across the study period were: Nassau (467 days), Suffolk (392 days), Westchester (354 days), New York (287 days), Herkimer (233 days), Oneida (186 days), Orange (186 days), Queens (186 days), Montgomery (184 days), and Albany (176 days) (Fig. 2A). The top ten PO counties according to the total number of PO division days across the study period were: Suffolk (5321 days), Nassau (4399 days), Westchester (3318 days), Orange (3139 days), Ulster (3077 days), Dutchess (2849 days), Erie (2426 days), Oneida (2124 days), Steuben (2109 days), and Sullivan (1980 days) (Fig. 2B).

Table 1 shows the rate ratios (RR) of hospital admissions for CVDs, chronic respiratory diseases, respiratory infections, and FWBD due to floods, PO, and their joint occurrence by lag days. Generally, the RRs for co-occurrence of floods and PO among these four diseases were higher than the RRs for floods or PO alone. For CVDs, the RR range for floods alone and PO alone were 1.01–1.04. For floods & PO combined, the RR was only statistically significant on lag 3 (RR (95% CI) = 1.13 (1.03, 1.24)). For chronic respiratory diseases, the RR for floods alone was only statistically significant on lag 6 (RR (95%CI) = 1.07 (1.02, 1.11)) and the RR range for PO alone was 1.02–1.16. For floods & PO combined, the significant RR range was 1.21–1.58. For respiratory infections, the RR range for floods alone was 1.03–1.11 and the RR range for PO alone was 1.05–1.15. For floods & PO combined, the RR range was 1.43–1.85. For FWBD, the significant RR range for floods alone was 1.08–1.18 and the RR range for PO alone was 1.08–1.21. For floods & PO combined, the significant RR range was 2.00–3.02. In the sensitivity analysis, by excluding

Hurricane Sandy, we found our results were robust and remained similar to our original findings.

Fig. 3 shows the RRs of hospital admissions for the four diseases due to the co-occurrence of floods and PO by different quantiles of PO coverage and lag days. Generally, health risks increased only when PO coverage exceeded the 75th percentile or 1.72%, which could be a health threshold. Larger scale PO was related to higher RRs, especially at the 90th percentile. For CVDs, the significant RR ranges for PO was 1.05–1.10, 1.05–1.08, 1.07–1.13, and 1.20–1.62 for the 25th, 50th, 75th, and 90th percentiles, respectively (Fig. 3A). For chronic respiratory diseases, the RR ranges for PO were 1.11–1.34, 1.14–1.45, 1.21–1.58, and 2.20–3.65 for the 25th, 50th, 75th, and 90th percentiles, respectively (Fig. 3B). For respiratory infections, the RR ranges for PO were 1.30–1.49, 1.37–1.60, 1.43–1.85, and 2.03–4.21 for the 25th, 50th, 75th, and 90th percentiles, respectively (Fig. 3C). For FWBD, the RR ranges for PO were 1.35–2.07, 1.41–2.15, 2.00–3.02, and 5.37 for the 25th, 50th, 75th, and 90th percentiles, respectively (Fig. 3D).

Table 2 shows the RRs of hospital admissions for the four diseases due to the co-occurrence of floods and PO by demographics. For CVDs, the largest significant RRs occurred for uninsured individuals (1.87 (1.17, 3.01)), followed by those insured through their employer (1.23), white individuals (1.11), females (1.11), and those >65 years old (1.09). For chronic respiratory diseases, the largest significant RRs occurred for Medicare recipients (2.11 (1.62, 2.75)), followed by those >65 years old (1.90), white individuals (1.82), females (1.69), males (1.57), and non-Hispanics (1.56). For respiratory infections, the largest significant RRs occurred for white individuals (1.87 (1.32, 2.65)), followed by females (1.82), those >65 years old (1.69), males (1.69), non-Hispanics (1.66), and Medicare recipients (1.66). For FWBD, the largest significant RRs occurred for Medicare recipients (2.88 (1.27, 6.53)), white individuals (2.75), and non-Hispanics

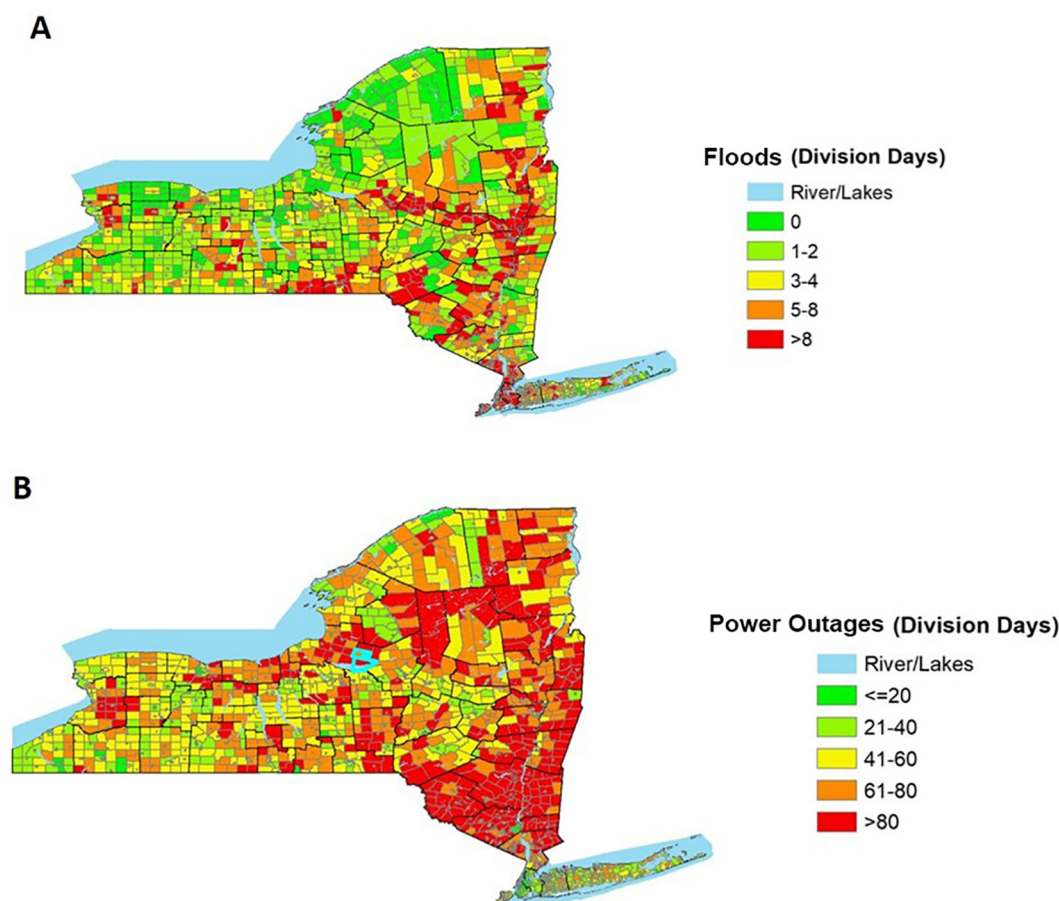


Fig. 2. Spatial distribution for floods and PO at the power-operating division level in NYS, 2002–2018. Panel A is for floods; panel B is for PO. Division days were defined as how many days of Floods or PO in a specific division.

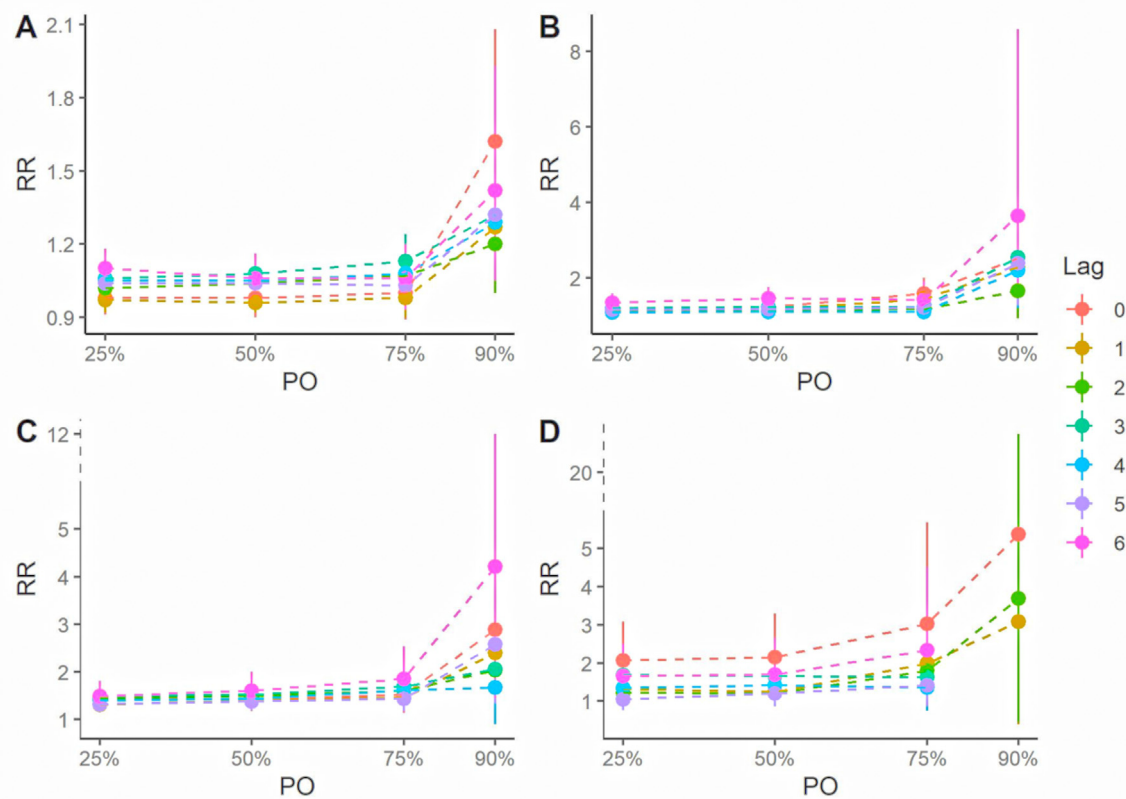


**Table 1**

Rate ratios<sup>a</sup> of hospital admissions of CVD, chronic respiratory diseases, respiratory infection diseases, and FWBD due to floods, PO, and joint occurrence by lag days in NYS, 2002–2018.

Lag		Floods & PO		Floods		PO	
		Case	RR (95% CI)	Case	RR (95% CI)	Case	RR (95% CI)
CVD	0	727,202	1.00 (0.89, 1.13)	2,131,433	1.03 (1.01, 1.06)	2,552,245	1.03 (1.01, 1.04)
	1	748,714	0.98 (0.90, 1.06)	2,191,105	1.01 (1.00, 1.02)	2,560,490	1.01 (1.00, 1.02)
	2	754,274	1.07 (0.99, 1.16)	2,210,990	1.00 (0.99, 1.02)	2,564,078	1.01 (1.00, 1.02)
	3	648,005	1.13 (1.03, 1.24)	2,204,313	1.01 (1.00, 1.03)	2,465,418	1.02 (1.01, 1.03)
	4	567,905	1.08 (0.99, 1.17)	2,208,905	1.01 (0.99, 1.02)	2,467,606	1.02 (1.01, 1.02)
	5	569,563	1.03 (0.95, 1.11)	2,189,441	1.01 (1.00, 1.03)	2,466,298	1.02 (1.01, 1.03)
	6	550,484	1.06 (0.93, 1.20)	2,167,738	1.04 (1.02, 1.06)	2,453,182	1.04 (1.02, 1.05)
Chronic respiratory diseases	0	127,022	1.58 (1.24, 2.00)	446,082	1.02 (0.98, 1.07)	580,705	1.16 (1.13, 1.19)
	1	125,681	1.44 (1.22, 1.70)	464,051	0.98 (0.96, 1.01)	584,667	1.08 (1.06, 1.10)
	2	126,763	1.17 (0.97, 1.42)	466,943	0.99 (0.97, 1.02)	582,540	1.05 (1.03, 1.06)
	3	86,992	1.23 (0.99, 1.54)	469,964	1.02 (0.99, 1.06)	539,911	1.05 (1.03, 1.07)
	4	90,441	1.09 (0.89, 1.34)	465,380	1.00 (0.97, 1.03)	539,130	1.02 (1.00, 1.04)
	5	92,209	1.21 (1.00, 1.47)	465,502	1.01 (0.98, 1.04)	536,598	1.03 (1.02, 1.05)
	6	79,110	1.41 (1.04, 1.91)	454,674	1.07 (1.02, 1.11)	531,084	1.10 (1.06, 1.13)
Respiratory infections	0	78,802	1.52 (1.13, 2.05)	326,284	1.09 (1.03, 1.15)	449,189	1.15 (1.12, 1.19)
	1	89,882	1.45 (1.18, 1.77)	341,336	1.03 (1.00, 1.06)	449,390	1.09 (1.07, 1.11)
	2	81,076	1.60 (1.29, 1.99)	346,827	1.03 (1.00, 1.06)	451,265	1.07 (1.05, 1.09)
	3	75,748	1.69 (1.34, 2.13)	351,845	1.06 (1.02, 1.10)	432,629	1.09 (1.06, 1.11)
	4	75,580	1.61 (1.30, 1.99)	353,583	1.04 (1.01, 1.08)	436,665	1.05 (1.03, 1.08)
	5	77,357	1.43 (1.17, 1.76)	347,679	1.04 (1.00, 1.07)	431,693	1.06 (1.04, 1.08)
	6	68,092	1.85 (1.35, 2.53)	334,791	1.11 (1.05, 1.17)	424,905	1.11 (1.08, 1.15)
FWBD	0	7971	3.02 (1.60, 5.69)	65,930	1.18 (1.06, 1.31)	89,014	1.21 (1.14, 1.29)
	1	12,426	2.00 (1.20, 3.32)	67,610	1.08 (1.01, 1.16)	92,218	1.11 (1.07, 1.15)
	2	9568	1.79 (0.98, 3.29)	70,520	1.09 (1.02, 1.17)	94,997	1.08 (1.04, 1.12)
	3	8691	1.63 (0.84, 3.16)	68,865	1.11 (1.03, 1.20)	88,940	1.12 (1.07, 1.17)
	4	7676	1.36 (0.75, 2.47)	69,874	1.05 (0.99, 1.13)	88,610	1.10 (1.06, 1.14)
	5	7676	1.42 (0.86, 2.34)	68,583	1.08 (1.01, 1.15)	87,469	1.11 (1.07, 1.15)
	6	8606	2.34 (1.21, 4.51)	62,658	1.17 (1.06, 1.30)	86,101	1.17 (1.10, 1.25)

<sup>a</sup> Adjusted for day of week, holidays, year, time, temperature, relative humidity, PM<sub>2.5</sub>, and O<sub>3</sub>.



**Fig. 3.** Rate ratios of hospital admissions of CVD (A), chronic respiratory diseases (B), respiratory infection diseases (C), and FWBD (D) due to joint occurrence of floods and PO in different quantile coverages by lag days in NYS, 2002–2018.

(2.33). Females, non-Hispanic individuals, white individuals, those >65 years old, Medicare recipients, and the uninsured might be more vulnerable than other demographics.

## 4. Discussion

### 4.1. PO and flood temporal trends and spatial patterns

We observed a significant increase in PO events over past 17 years while the increase of floods was not prominent. There was a spatial cluster of PO events in the counties of Ulster, Putnam, Dutchess, Sullivan, Greene, Columbia, and Orange (Hudson Valley) in NYS. Consistently, Eto et al. found that the rate of PO or interruptions had increased by 2% each year over the past 10 years (Eto et al., 2021). According to Jordan et al. (2014), the five-year annual average of PO doubled every five years (Wirfs-Brock, 2021). We found that the PO-frequent counties or power-operating divisions were more centered in southern NYS. According to Chrobark et al. (2020), the lack of crucial maintenance, refusal to upgrade, focus on profit instead of customers, and an aging, frail, and vulnerable electricity infrastructure could be the main reasons for more frequent and severe PO (Chrobak, 2020). Unless this issue is systematically addressed, the propensity and impact of these events will continue to increase. Moreover, the U.S. EPA reported that the frequency of floods in 2010–2020 was significantly higher than that in 1990–2009 (U.S. EPA, n.d.). However, the increase of flood events was not prominent in NYS, probably due to the shorter study period than in the EPA data.

### 4.2. Independent and synergistic effects of PO and floods

We identified significant increased health risks associated with both the independent effects from PO and floods and their synergistic effects. Specifically, the magnitudes of health risks from PO seemed to be higher than those from floods. Furthermore, comparing with independent effects from floods or PO alone, the health risks for all four diseases studied during the co-occurrence of both floods and PO were almost three to fifteen times higher. In addition, our findings were robust after excluding Hurricane Sandy. Consistently, a review paper reported that floods or PO alone was significantly related to the increases in hospital admissions (Lane et al., 2013). For example, Becquart et al. reported that hospitalization rates for CVD after Hurricane Katrina increased from 11.25 to 18.5 cases/day per 10,000 for older adults (NA B, 2018). However, no prior studies examined the joint effect between PO and floods because they mainly focused on one single large flood or hurricane event (D E, 2013; Mab et al., 2019; NA B,

2018; B R, 2011), which was usually accompanied by a PO. The stronger synergistic impact of PO and floods on health compared to their independent effects was first identified in this study. The concurrence of both floods and PO may indicate that the largest floods that co-occur with PO were strong enough to cause many environmental and health problems, but floods or PO alone may represent isolated or small PO or flood events that have less of an impact on health. Our prior studies in NYS that linked PO and various storm events with health outcomes consistently demonstrated the stronger synergistic effect between PO and other natural disasters on health than the effects from PO or storm events alone (Sheridan et al., 2021; Lin et al., 2021).

### 4.3. Risks of PO and floods by diseases, lag, and SES

Immediate health impacts of the co-occurrence of PO and floods were found in chronic respiratory diseases and FWBD, while late-onset risks were observed in CVD and respiratory infections in this study, which is biologically possible. Zhang et al. found that PO could be an immediate risk factor for COPD exacerbations due to the interruption of mechanical ventilation and medication nebulizers (Zhang et al., 2020). In addition, drinking water contamination, sewage overflow, and bad hygiene conditions during a flood event could also explain the quick onset of food poisoning for FWBD and the late treatment of respiratory infections (Lane et al., 2013). Moreover, Becquart et al. observed a peak increase for CVD at lag 6 day and hypothesized that the late risk for CVD was probably due to the psychosocial and post-traumatic stress (NA B, 2018). Among the Hurricane Katrina survivors, Donald et al. observed that 24% had PTSD, 46% had depression, 50% died of CVD, and 60% were hospitalized due to CVD-related causes (D E, 2013).

Female, Non-Hispanic, white, older people, and those without medical insurance seemed to be more vulnerable during floods and PO in this study but were not statistically significant. Kessler et al. (2008) and JS P (2010) also found that women were more vulnerable when exposure to Hurricane Katrina, and they suffered severe mental disorders after the disaster. Consistently, several studies observed that older people had more respiratory hospital admissions and were more vulnerable to diarrhea or waterborne diseases after PO or disasters (S L, 2011; Anderson and Bell, 2012; J B, 2008; SN J, 2009; Rygel et al., 2006; K D, 2014). Unexpectedly, we found higher risks of non-Hispanic and white in CVD, respiratory diseases, and FWBD. However, Zhang et al. also found that non-blacks had higher risk for PO in COPD hospitalizations (Zhang et al., 2020). Consistently, Lin et al. reported that whites and non-Hispanics had higher risks for respiratory admissions during the Northeastern blackout (S L, 2011).

**Table 2**

Rate ratios<sup>a</sup> of hospital admissions of CVD, chronic respiratory diseases, respiratory infections, and FWBD due to joint occurrence by demographics in NYS, 2002–2018<sup>b</sup>.

Group		CVD		Chronic respiratory diseases		Respiratory infection diseases		FWBD	
		Case	RR (95% CI)	Case	RR (95% CI)	Case	RR (95% CI)	Case	RR (95% CI)
Gender	Female	521,639	1.11 (1.00, 1.22)	108,573	1.69 (1.30, 2.21)	66,994	1.82 (1.28, 2.59)	8114	2.02 (0.86, 4.73)
	Male	584,259	1.06 (0.97, 1.16)	75,473	1.57 (1.14, 2.16)	57,350	1.69 (1.14, 2.50)	2233	1.99 (0.69, 5.72)
Ethnicity	Hispanic	54,364	1.10 (0.80, 1.51)	16,063	0.85 (0.34, 2.13)	8853	0.46 (0.09, 2.35)	–	–
	Non-Hispanic	1,074,394	1.06 (0.99, 1.13)	179,540	1.56 (1.27, 1.92)	130,474	1.66 (1.27, 2.16)	10,661	2.33 (1.36, 3.97)
Race	White	701,810	1.11 (1.01, 1.21)	93,616	1.82 (1.37, 2.40)	72,144	1.87 (1.32, 2.65)	5411	2.75 (1.32, 5.74)
	Black	245,863	1.05 (0.92, 1.21)	65,777	1.20 (0.83, 1.74)	31,253	1.48 (0.85, 2.58)	3352	0.82 (0.17, 4.05)
	Asian	50,483	0.90 (0.71, 1.14)	4634	0.36 (0.08, 1.61)	4803	0.53 (0.14, 2.07)	466	1.26 (0.21, 7.48)
	Other	135,218	1.09 (0.91, 1.30)	22,468	1.11 (0.60, 2.06)	12,832	1.45 (0.63, 3.34)	–	–
Age	<18	– <sup>c</sup>	–	29,388	0.98 (0.52, 1.86)	11,046	2.23 (0.98, 5.08)	932	1.48 (0.12, 17.67)
	18–45	40,943	1.23 (0.89, 1.70)	10,882	0.89 (0.29, 2.73)	3583	1.68 (0.40, 7.01)	–	–
	46–65	335,374	1.07 (0.95, 1.20)	43,200	1.36 (0.89, 2.08)	18,200	1.46 (0.70, 3.06)	1145	1.49 (0.24, 9.11)
	>65	705,542	1.09 (1.00, 1.19)	78,503	1.90 (1.44, 2.50)	75,471	1.69 (1.21, 2.37)	3199	1.83 (0.66, 5.05)
Insurance	Self-paid	19,208	1.87 (1.17, 3.01)	1079	3.77 (0.47, 30.17)	–	–	–	–
	Medicare	631,571	1.05 (0.96, 1.15)	71,148	2.11 (1.62, 2.75)	63,293	1.66 (1.16, 2.36)	3849	2.88 (1.27, 6.53)
	Medicaid	81,977	1.09 (0.86, 1.37)	16,319	0.70 (0.29, 1.70)	11,874	1.71 (0.61, 4.78)	–	–
	Company	237,751	1.23 (1.07, 1.42)	48,355	1.20 (0.75, 1.93)	24,929	1.73 (0.93, 3.22)	4007	1.08 (0.46, 2.52)
	Other	72,858	1.23 (0.97, 1.56)	6198	1.78 (0.76, 4.15)	1575	1.64 (0.44, 6.14)	474	3.57 (0.58, 21.88)

<sup>a</sup> Adjusted for day of week, holidays, year, time, temperature, relative humidity, PM<sub>2.5</sub>, and O<sub>3</sub>.

<sup>b</sup> Rate ratio for CVD is on lag 3; for chronic respiratory diseases is on lag 0; for respiratory infection diseases is on lag 6; and FWBD is on lag 0.

<sup>c</sup> Model does not converge.

The possible explanations include a higher percentage of whites living in beach houses, better access to care, and a much larger sample size than other groups. Another important finding is that people without insurance (self-pay) had significantly higher health risks after PO/floods than those with insurance, thereby suggesting that poverty may play an important role in disaster preparedness (BM R, 2013; WR D, 2018).

#### 4.4. Different coverage of PO with floods

We observed an interesting fact that larger scale PO together with floods were related to much larger risks of hospital admission for these four diseases. Compared with low PO coverage (i.e.,  $\leq 25$  percentile or PO coverage  $> 0.03\%$ ), the elevated health risks were almost double for PO coverage that exceeded the 75th percentile (or PO coverage  $> 1.72\%$ ) and four to ten times higher for PO coverage that exceeded the 90th percentile (or PO coverage  $> 12.06\%$ ). Another very interesting finding is that the risks for all four diseases start at  $\geq 75$ th percentile or PO coverage  $> 1.72\%$ , which could be an important threshold for health risks after PO/floods. Consistently, Christine et al. (2018) also defined the PO occurrence as 1000 customers out in the warm season (PO coverage =  $0.08\%–2.97\%$ ) and 75 customers out (PO coverage =  $0.004\%–0.28\%$ ) in the cold season (Dominianni et al., 2018). Our threshold was covered by Christine's study during the warm season (Dominianni et al., 2018). Based on our “dose-response” relationship curve, our study provided additional and robust evidence that the larger scale PO in combination with floods was associated with a bigger impact on health outcomes, especially when PO coverage exceeded about 2%.

#### 4.5. Strengths and limitations

To our knowledge, the current study is among the few studies investigating the synergistic impacts of PO and floods. This study covered NYS in its entirety and a long time period from 2002 to 2018 by linking large hospital admission data (42.7 million) with a unique and complete PO database. Our findings fill current knowledge gaps by highlighting the important independent role and synergistic impacts of PO with flood events, identifying a potential health risk threshold of PO, and providing additional evidence to identify vulnerable groups. Our findings suggested that electricity is very essential to the risk management during a disaster such as floods and should be one of the top priorities in disaster preparedness. Improving power system resiliency could be a very effective way to alleviate the burden of hospitals during flood events.

However, some limitations should also be acknowledged. This study only included the hospital admission cases, which were the most severe cases. These four diseases require immediate care and treatment. Another potential limitation was that some confounders such as access to medical care, housing and food insecurity, homelessness, loss of insurance, and loss of income may impact our findings. However, as our analysis was performed at each power operating division using pre-/post-PO or floods comparison, these sociodemographic factors in the same area should not have changed much between pre-/post-PO or flood periods, and therefore, part of the confounding effects of these factors on the exposure-health associations examined could be controlled by the design. Furthermore, we conducted stratified analyses by different sociodemographic characteristics, including age, gender, race, ethnicity, and whether people had health insurance. In addition, the population distribution would be different in different operating divisions, but the flood/PO-health associations were evaluated within the same power operating division in this study. Because there have been no significant changes in the population composition in NYS during the study period, the population distribution should not have a substantial impact on our findings.

## 5. Conclusion

Hospital admissions of CVD, chronic respiratory diseases, respiratory infections, and FWBD were significantly associated with PO or floods alone.

These associations were much stronger during the co-occurrence of PO and floods, especially when PO coverage exceeded 1.72%. Females, non-Hispanics, whites, older adults, and uninsured people might be more vulnerable to PO-flood events. This study provided useful information for emergency preparedness, disaster management, and recovery plans after floods with PO.

## Disclaimer

This publication was produced from raw data purchased from or provided by the NYSDOH. However, the conclusions derived, and views expressed herein are those of the author(s) and do not reflect the conclusions or views of NYSDOH. NYSDOH, its employees, officers, and agents make no representation, warranty or guarantee as to the accuracy, completeness, currency, or suitability of the information provided here.

## CRediT authorship contribution statement

**Xinlei Deng:** Conceptualization, Software, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization. **Samantha Friedman:** Writing - original draft, Writing - review & editing. **Ian Ryan:** Writing - original draft, Writing - review & editing. **Wangjian Zhang:** Conceptualization. **Guanghui Dong:** Writing - review & editing. **Havidan Rodriguez:** Writing - review & editing. **Fangqun Yu:** Writing - review & editing. **Wenzhong Huang:** Writing - review & editing. **Arshad Nair:** Writing - review & editing. **Gan Luo:** Writing - review & editing. **Shao Lin:** Conceptualization, Methodology, Resources, Writing - review & editing, Supervision, Project administration, Funding acquisition.

## Declaration of competing interest

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

## Acknowledgement

This work was supported by Grant # 1R15ES0280001A1 from the National Institute of Environmental Health Sciences of United States. We thank the NYSDOH for providing the comprehensive health data (data sharing protocol number: 1509-01 A), and the NYS Department of Public Service for providing the statewide PO data.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.154305>.

## References

- American Society of Civil Engineers, 2017. A comprehensive assessment of America's infrastructure. Accessed October 20, 2021. [Infrastruct Rep Card. https://www.infrastructurereportcard.org/wp-content/uploads/2016/10/2017-Infrastructure-Report-Card.pdf](https://www.infrastructurereportcard.org/wp-content/uploads/2016/10/2017-Infrastructure-Report-Card.pdf).
- Anderson, G.B., Bell, M.L., 2012. Lights out: impact of the august 2003 power outage on mortality in New York, NY. *Epidemiology* 23 (2), 189. <https://doi.org/10.1097/EDE.0B013E318245C61C>.
- Andrade, L., O'Dwyer, J., O'Neill, E., Hynds, P., 2018. Surface water flooding, groundwater contamination, and enteric disease in developed countries: a scoping review of connections and consequences. *Environ. Pollut.* 236, 540–549. <https://doi.org/10.1016/J.ENVPOL.2018.01.104>.
- B R, 2011. Adverse respiratory symptoms and environmental exposures among children and adolescents following Hurricane Katrina. *Public Health Rep.* 126 (6), 853–860. <https://doi.org/10.1177/003335491112600611>.
- BM R, 2013. Social capital and disaster preparedness among low income Mexican Americans in a disaster prone area. *Soc. Sci. Med.* 83, 50–60. <https://doi.org/10.1016/J.SOCSCIMED.2013.01.037>.

- Casey, J.A., Fukurai, M., Hernández, D., Balsari, S., Kiang, M.V., 2020. Power outages and community health: a narrative review. *Curr. Environ. Heal Rep.* 7 (4), 371–383. <https://doi.org/10.1007/S40572-020-00295-0>.
- Chakalian, P.M., Kurtz, L.C., Hondula, D.M., 2019. After the lights go out: household resilience to electrical grid failure following hurricane Irma. *Nat. Hazards Rev.* 20 (4), 05019001. [https://doi.org/10.1061/\(ASCE\)NH.1527-6996.0000335](https://doi.org/10.1061/(ASCE)NH.1527-6996.0000335).
- Christenson, B., Fuxench, Z., Morales, J.A., Suárez-Villamil, R.A., Souchet, L.M., 2003. Severe community-acquired pneumonia and sepsis caused by *Burkholderia pseudomallei* associated with flooding in Puerto Rico. Accessed February 21, 2022 *Bol. Asoc. Med. P. R.* 95 (6), 17–20. <https://europepmc.org/article/med/15449787>.
- Chrobak, U., 2020. The US has more power outages than any other developed country. Here's why. Accessed October 20, 2021 *Popular Science*. <https://www.popsoci.com/story/environment/why-us-lose-power-storms/>.
- CRAN - Package metafor. Accessed February 21, 2022. <https://cran.r-project.org/web/packages/metafor/index.html>.
- De E, 2013. Association of posttraumatic stress disorder and depression with all-cause and cardiovascular disease mortality and hospitalization among Hurricane Katrina survivors with end-stage renal disease. *Am. J. Public Health* 103 (4). <https://doi.org/10.2105/AJPH.2012.301146>.
- Dominiani, C., Lane, K., Johnson, S., Ito, K., Matte, T., 2018. Health impacts of citywide and localized power outages in New York City. *Environ. Health Perspect.* 126 (6). <https://doi.org/10.1289/EHP2154>.
- Eto, J., Larsen, P., Todd, A., Fisher, E., LaCommare, K., 2021. An examination of temporal trends in electricity reliability based on reports from U.S. electric utilities. Accessed October 20 *Electricity Markets and Policy Group*. <https://emp.lbl.gov/publications/examination-temporal-trends>.
- Gasparrini, A., 2011. Distributed lag linear and non-linear models in R: the package dlnm. *J. Stat. Softw.* 43 (8), 2–20. <https://doi.org/10.18637/jss.v043.i08>.
- J B, 2008. Hurricane Katrina deaths, Louisiana, 2005. *Disaster Med. Public Health Prep.* 2 (4), 215–223. <https://doi.org/10.1097/DMP.0B013E31818AAAF55>.
- JS P, 2010. Hurricane Katrina and mental health: a research note on Mississippi Gulf Coast residents. *Sociol. Inq.* 80 (3), 513–524. <https://doi.org/10.1111/J.1475-682X.2010.00345.X>.
- K D, 2014. Using Medicare data to identify individuals who are electricity dependent to improve disaster preparedness and response. *Am. J. Public Health* 104 (7), 1160–1164. <https://doi.org/10.2105/AJPH.2014.302009>.
- Kenward, A., Raja, U., 2014. Blackout: extreme weather, climate change and power outages. *Clim. Cent.* <https://assets.climatecentral.org/pdfs/PowerOutages.pdf>. (Accessed 4 March 2022).
- Kessler, R.C., Galea, S., Gruber, M.J., Sampson, N.A., Ursano, R.J., Wessely, S., 2008. Trends in mental illness and suicidality after hurricane Katrina. *Mol. Psychiatry* 13 (4), 374. <https://doi.org/10.1038/SJ.MP.4002119>.
- KK J-A, 2014. A comparison of carbon monoxide exposures after snowstorms and power outages. *Am. J. Prev. Med.* 46 (5), 481–486. <https://doi.org/10.1016/J.AMEPRE.2014.01.006>.
- Klein, K.R., Herzog, P., Smolinske, S., White, S.R., 2007. Demand for poison control center services “surged” during the 2003 blackout. *Clin. Toxicol. (Phila.)* 45 (3), 248–254. <https://doi.org/10.1080/15563650601031676>.
- Lane, K., Charles-Guzman, K., Wheeler, K., Abid, Z., Graber, N., Matte, T., 2013. Health effects of coastal storms and flooding in urban areas: a review and vulnerability assessment. *J. Environ. Public Health* 2013. <https://doi.org/10.1155/2013/913064>.
- Li, L., Ma, Z., Cao, T., 2020. Leveraging social media data to study the community resilience of New York City to 2019 power outage. *Int. J. Disaster Risk Reduct.* 51, 101776. <https://doi.org/10.1016/J.IJDRR.2020.101776>.
- Lin, S., Zhang, W., Sheridan, S., et al., 2021. The immediate effects of winter storms and power outages on multiple health outcomes and the time windows of vulnerability. *Environ. Res.* 196, 110924. <https://doi.org/10.1016/J.ENVRES.2021.110924>.
- Mab, C., Aj, F., Sa, C., et al., 2019. Health impact of hurricanes Irma and Maria on St. Thomas and St. John, US Virgin Islands, 2017–2018. *Am. J. Public Health* 109 (12), 1725–1732. <https://doi.org/10.2105/AJPH.2019.305310>.
- Mukherjee, S., Nateghi, R., Hastak, M., 2018. A multi-hazard approach to assess severe weather-induced major power outage risks in the U.S. *Reliab. Eng. Syst. Saf.* 175, 283–305. <https://doi.org/10.1016/J.RESS.2018.03.015>.
- Musacchio, A., Andrade, L., O'Neill, E., Re, V., O'Dwyer, J., Hynds, P.D., 2021. Planning for the health impacts of climate change: flooding, private groundwater contamination and waterborne infection – a cross-sectional study of risk perception, experience and behaviours in the Republic of Ireland. *Environ. Res.* 194, 110707. <https://doi.org/10.1016/J.ENVRES.2021.110707>.
- NA B, 2018. Cardiovascular Disease Hospitalizations in Louisiana Parishes' Elderly before, during and after Hurricane Katrina. *Int. J. Environ. Res. Public Health* 16 (1). <https://doi.org/10.3390/IJERPH16010074>.
- NOAA, 2020. U.S. Billion-dollar Weather and Climate Disasters, 1980 - Present. *Natl. Centers Environ. Inf.* Published. <https://doi.org/10.25921/STKW-7W73> online.
- Quist, A.J.L., Fliss, M.D., Wade, T.J., Delamater, P.L., Richardson, D.B., Engel, L.S., 2022. Hurricane flooding and acute gastrointestinal illness in North Carolina. *Sci. Total Environ.* 809, 151108. <https://doi.org/10.1016/J.SCITOTENV.2021.151108>.
- Rocque, R.J., Beaudoin, C., Ndjaboue, R., et al., 2021. Health effects of climate change: an overview of systematic reviews. *BMJ Open* 11 (6), e046333. <https://doi.org/10.1136/BMJOPEN-2020-046333>.
- Rygel, L., O'Sullivan, D., Yarnal, B., 2006. A method for constructing a social vulnerability index: an application to hurricane storm surges in a developed country. *Mitig. Adapt. Strateg. Glob. Chang.* 11 (3), 741–764. <https://doi.org/10.1007/S11027-006-0265-6> 2006 113.
- S L, 2011. Health impact in New York City during the Northeastern blackout of 2003. *Public Health Rep.* 126 (3), 384–393. <https://doi.org/10.1177/003335491112600312>.
- S L, 2016. What happened to our environment and mental health as a result of hurricane sandy? *Disaster Med. Public Health Prep.* 10 (3), 314–319. <https://doi.org/10.1017/DMP.2016.51>.
- Sheridan, S.C., Zhang, W., Deng, X., Lin, S., 2021. The individual and synergistic impacts of windstorms and power outages on injury ED visits in New York State. *Sci. Total Environ.* 797, 149199. <https://doi.org/10.1016/J.SCITOTENV.2021.149199>.
- Smith, A., 2010–2019. A landmark decade of U.S. billion-dollar weather and climate disasters. Accessed October 20, 2021 *NOAA Climate.gov*. <https://www.climate.gov/news-features/blogs/beyond-data/2010-2019-landmark-decade-us-billion-dollar-weather-and-climate>.
- SN J, 2009. Loss of life caused by the flooding of New Orleans after Hurricane Katrina: analysis of the relationship between flood characteristics and mortality. *Risk Anal.* 29 (5), 676–698. <https://doi.org/10.1111/J.1539-6924.2008.01190.X>.
- Tonn, G.L., Guikema, S.D., Ferreira, C.M., Quiring, S.M., 2016. Hurricane Isaac: a longitudinal analysis of storm characteristics and power outage risk. *Risk Anal.* 36 (10), 1936–1947. <https://doi.org/10.1111/RISA.12552>.
- U.S. Energy Information Administration (US EIA), 2018. Average frequency and duration of electric distribution outages vary by states - Today in Energy. Accessed October 20, 2021 *U.S. Energy Information Administration (EIA)*. <https://www.eia.gov/todayinenergy/detail.php?id=35652>.
- U.S. EPA. Climate change indicators: coastal flooding. <https://www.epa.gov/climate-indicators/climate-change-indicators-coastal-flooding>.
- Wirfs-Brock, J., 2021. Power outages on the rise across the U.S. Accessed October 20 *Inside Energy*. <http://insideenergy.org/2014/08/18/power-outages-on-the-rise-across-the-u-s/>.
- WR D, 2018. Ethnicity, income, and disaster preparedness in Deep South Texas, United States. *Disasters* 42 (4), 719–733. <https://doi.org/10.1111/DISA.12277>.
- Zhang, W., Sheridan, S.C., Birkhead, G.S., et al., 2020. Power outage: an ignored risk factor for COPD exacerbations. *Chest* 158 (6), 2346–2357. <https://doi.org/10.1016/J.CHEST.2020.05.555>.