**Assessing potential sources of bias in measuring power outage exposure with simulations**

**Heather McBrien1, Dan Mork2, Marianthi-Anna Kioumourtzoglou1, Joan Casey3**

**1 Columbia Mailman School of Public Health, Department of Environmental Health Sciences**

**2 Harvard T.H.Chan School of Public Health, Department of Biostatistics**

**3 University of Washington Department of Environmental and Occupational Health Sciences**

**Structured abstract:**

Background: Power outages pose serious health risks to vulnerable groups, however, the relationship between power outage exposure and health outcomes is understudied due to lack of exposure data. Though new national data on power outage exposure is now available, there are still exposure measurement challenges. Power outage exposure data are missing larger percentages of observations. There is also no information in the literature about health relevant duration of power outages. Incorrect assumptions about health relevant duration of power outages and missing exposure data could bias results of epidemiological studies of power outage and health.

Objective: We conducted simulations to measure the magnitude and direction of bias introduced into a study of power outage exposure and a health outcome from wrong assumptions about the health-relevant duration of power outage, and missing data.

Methods: We conducted a simulation representing a national county-level study of power outage exposure and hospitalizations, where simulated and then estimated the effect of daily power outage exposure on hospitalization rates.

We measured the magnitude and direction of bias introduced in two scenarios. First, where the researcher made incorrect assumptions about the health-relevant duration of power outage, and second, where increasing amounts of exposure data were missing.

Results: In scenarios where the researcher underestimated the health-relevant duration of power outage, results of an epidemiolocal study of power outage and hospitalizations were substantially biased downward, while overestimating the health-relevant duration of power outage resulted in minimal bias. When 50% of person-time of exposure data was missing or more, results were substantially biased downward. With fewer data missing, results were minimally biased.

Significance: Appropriate sensitivity analyses testing assumptions about the health-relevant duration of power outage, along with restricting analyses to areas with good coverage of exposure measurement can help researchers leverage available power outage data to get reasonable effect estimates in studies of power outage and health outcomes.

**Introduction:**

Power outages are becoming more common.[[1]](#endnote-1),[[2]](#endnote-2) Climate change has increased the frequency and intensity of extreme weather, such as heat, wind, and precipitation.[[3]](#endnote-3),[[4]](#endnote-4),[[5]](#endnote-5) Aging grid components and have not been modernized to withstand these previously rare severe weather events.[[6]](#endnote-6),[[7]](#endnote-7),[[8]](#endnote-8) As a result, US electrical customers experienced an average of 8 hours without power in 2020, the longest duration on record.[[9]](#endnote-9)

Power outages pose serious health risks to vulnerable people. For those who use electricity-dependent medical equipment such as at-home ventilators and oxygen tanks, loss of electricity can be life-threatening.[[10]](#endnote-10) In children, outages can increase accidents and injuries related to generator, natural gas, and candle use.[[11]](#endnote-11),[[12]](#endnote-12),[[13]](#endnote-13) Power outages can render air conditioners, heaters, and tap water unavailable, resulting in heat exposure, cold exposure, and dehydration. Older adults are especially susceptible to stroke, myocardial infarction, chronic obstructive pulmonary disease (COPD) exacerbation, and other adverse cardiorespiratory outcomes following such exposures.[[14]](#endnote-14),[[15]](#endnote-15),[[16]](#endnote-16),[[17]](#endnote-17)

Despite the health risks of power outages, data describing power outage exposure are extremely limited,[[18]](#endnote-18),[[19]](#endnote-19) constraining research. To our knowledge, only one US-based dataset describes outage exposure across space and time at a sub-county spatial scale, covering only New York State.[[20]](#endnote-20) This dataset has allowed for evaluation of the impact of power outages on health.[[21]](#endnote-21),[[22]](#endnote-22),[[23]](#endnote-23),[[24]](#endnote-24),[[25]](#endnote-25) However, almost all published studies of power outages to date rely on this single dataset,[[26]](#endnote-26) meaning results are specific to New York State and may not be generalizable. The remaining studies of outage and health use large-scale events such as single hurricanes or other disasters that disrupted power as a surrogate for the timing of power outage exposure in specific locations.[[27]](#endnote-27),[[28]](#endnote-28) These studies consider everyone in a city or county exposed to the power outage in the hours, days, or weeks following the index event. Unfortunately, studies based on single climate hazard events cannot disentangle the health effects of power outage exposure from simultaneous severe weather exposure, and they cannot be used to estimate exposure-response relationships between the severity power outages and health. This would require the measurement of power outage exposure by spatial unit over time.

Quantifying the health risks and costs associated with power outages can influence energy policy decisions. If power outages cause significant morbidity and mortality, improving grid infrastructure, community solar power, electricity storage, and electricity reliability could cost-effectively improve community health. Knowing the health risks of power outages can also motivate interventions in vulnerable populations to prevent adverse health outcomes.[[29]](#endnote-29)

In our previous work, we created a new national dataset of hourly power outage exposure by county in the continental United States[[30]](#endnote-30) (the PowerOutages.us dataset, or POUS dataset). This dataset will allow researchers to characterize exposure-response relationships between power outage and health outcomes nationally, by region, and within vulnerable populations.

However, even with these new data, major challenges with exposure assessment remain. First, there is no established strategy to measure health-relevant power outage exposure in the literature.[[31]](#endnote-31) Power outage is not a spatially continuous exposure, like air pollution or heat exposure. Individual households or grid connections in the same area may not experience power outages at the same time. However, the only data currently available to measure power outage (the POUS and New York State datasets) are counts of customers without power by hour at the spatial unit level, which can be interpreted in multiple ways. When assessing spatial unit level exposure, researchers must pick a cut point (a percent of customers in a community without power) after which an area is considered exposed to power outage. They must also consider and define the duration of power outage: how long does an outage need to last for a spatial unit to be exposed? A single strategy to describe power outage exposure would allow comparability and pooling of results across studies.

Second, the health-relevant duration of power outage matters for exposure assessment. Many existing studies examine outages of a specific length (ex. 8+ hours).[[32]](#endnote-32) However, we are not aware of literature describing how long power outages must last to cause adverse health outcomes. There are likely threshold effects: power outages longer than a certain duration may increase risk of an adverse health outcome, but shorter outages may not. For example, 8+ hour power outages may affect the health of those using oxygen tanks and at-home ventilators if device batteries die after 8 hours of power outage, while shorter outages may have no effect. Incorrect assumptions about the health-relevant duration can potentially bias the results of epidemiological studies of power outages and health outcomes.

Finally, both the New York State and POUS datasets are missing large percentages of observations[[33]](#endnote-33),[[34]](#endnote-34), with some counties in POUS missing data on up to 70% of county-hours. In the POUS dataset, data are missing if utilities did not have a website or if utility websites were offline or unscrapable for long periods of time (months or years), since information in this dataset comes from scraping utility company websites. In these cases, imputing missing values is nearly impossible because no data exist from which to draw information. To reduce exposure misclassification, researchers could exclude counties that are missing more than a specified percentage of observations from epidemiological studies.

In this paper, we aimed to address these exposure measurement issues. First, we developed a strategy for measuring power outage exposure. Then, we ran simulations to address two other potential sources of bias: incorrect assumptions about the health-relevant outage duration and exposure misclassification from missing data. We quantified the magnitude and direction of bias introduced when researchers assumed a certain length of power outage (for example, 8+ hours) caused adverse health outcomes, but outages of a different length (for example, 4+ hours) were the correct health-relevant exposure duration. To deal with missing data, we used simulations to identify a percentage cut-point, above which if a county had more missingness, this missingness would (potentially severely) bias outage-health effect estimates. We tested the sensitivity of simulation results to effect size and study design, across effect sizes estimated by previous studies of power outage and health outcomes, and across study designs we imagine researchers could use to conduct epidemiologic studies of power outage and health outcomes.

Our results contribute to the power outage and health literature with recommendations for consistently defining and measuring power outage exposure, using the datasets currently available, while minimizing potential bias in future epidemiological studies. Our results also inform the interpretation of previous studies conducted with these existing power outage exposure datasets.

**Methods:**

**Power outage datasets**

In our previous work, we purchased raw power outage data from PowerOutages.us and created a national county-level hourly dataset of power outage exposure[[35]](#endnote-35) (the POUS dataset). Most utility websites report the number of customers without power by neighbourhood or city in real-time. PowerOutages.us compiled these data by scraping counts of customers without power from utility website APIs covering the continental US in real-time every hour from 2018–2020.[[36]](#endnote-36) We used this compilation to produce the hourly county-level POUS dataset.[[37]](#endnote-37)

The POUS dataset contained hourly counts of customers without power for US counties (n = 2,447 [78%]) from January 1st, 2018, to December 31st, 2020. Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business.[[38]](#endnote-38) Counts of customers without power (henceforth, “customers out”) reported in this dataset do not necessarily track the same customers: if 10 customers are reported out in two subsequent hours in one county, the data do not contain information about whether the same 10 customers lacked power or if, for example, 10 customers were without power in the first hour and a different 10 customers were without power in the second hour, meaning 20 customers were without power for 1 hour each.

The New York State power outage dataset (NYS dataset) is structured similarly – counts of customers without power are reported every 30 minutes by power operating division.[[39]](#endnote-39),[[40]](#endnote-40) Power operating divisions (n = 1,865) are geographic units varying in size but similar to ZIP codes throughout the state.

**Strategy to measure power outage**

The available power outage exposure data is continuous; again, the POUS dataset contains counts of customers without power for each hour. When studying power outage exposure and health outcomes, researchers could relate spatial-unit level daily or hourly customer-hours without power to health outcomes. However, ‘customer-hours without power’ is not a well-defined measurement of exposure. It is two-dimensional – it captures the number of customers without power, and also the duration of outages. If one spatial unit-day has 100 customer hours without power, this could mean that 10 customers were without power for 10 hours, or 1000 customers were without power for 10 minutes in that spatial unit on that day. These two scenarios would likely have different consequences for health.

Because customer-hours without power is not well-defined, it would be difficult to interpret the meaning of effect estimates from a study using this exposure measurement, or shape policy based on this exposure measurement. In our proposed strategy to measure power outage, we aimed to summarize continuous counts of customers without power so that we captured both dimensions of area-level power outage exposure: the magnitude of outage (how many customers are affected) and the duration (for how long).

To determine if a county-day was exposed to a power outage, we first considered each hour alone. We considered a county-hour exposed to a power outage if the percentage of customers without power in county *i* during hour *j* exceeded an arbitrary cut point *k%* —for example, 10% of county customers. In this example, we would define a county *i* exposed to a power outage during hour *j* if more than 10% of customers served in county *i* were without power. Then, we chose a health-relevant duration *d* (for example, *d* = 8 hours). *d* could be any duration specified by the researcher. We summarized to the daily level, and considered a county-day as exposed if there were at least 8 consecutive hours of ‘power outage on’ (>*k*% customers out in county *i*) in that county on that day or ending on that day (**Figure 1**).

When a county is exposed to an 8+ hour power outage according to this definition, it does not necessarily mean that 10% (or another specified *k*%) of people in that county were without power for at least 8 hours that day. One customer can represent many people, and individual customers are not tracked over time. Therefore, an 8+ hour outage affecting 10% of customers indicates that at least 10% of customers in a spatial unit were without power for 8+ hours that day. Therefore, this is an aggregate spatial unit-level exposure definition rather than an individual-level one.

Exposure misclassification is inherent in this definition. When the county is considered exposed, some customers in the county will be without electricity (at least *k*%), and others will still have electricity. Other studies of power outage exposure using a similar exposure definition have handled this exposure misclassification by conducting sensitivity analyses varying the cut point *k* above which a spatial unit is considered exposed to power outage. For example, Northrop et al. considered a spatial unit exposed to power outage if more than 10% of the customers served in that unit were without power, and conducted two sensitivity analyses using cut points at 20% and 30%.[[41]](#endnote-41) As the cut point percentage increases, the number of customers incorrectly identified as exposed decreases, and the specificity of this definition of power outage improves.

Here, we propose using this strategy for measuring power outage exposure, while always conducting a sensitivity analysis on the percentage out cut point.

**Simulation design**

**Overview**

We designed a simulation representing an epidemiological study measuring the association between power outage exposure and hospitalization rates. This study is meant to mimic a study that could be conducted using the POUS data. The outcome of ‘hospitalizations’ is intentionally vague and could be any count health outcome hypothesized to be caused or exacerbated by power outages. We simulated daily binary power outage exposure for 100 US counties for one year and daily county-level hospitalization rates for these counties over the same period. We generated effect estimates of power outage exposure on hospitalization under a zero-bias scenario and then in scenarios representing incorrect assumptions about the health-relevant power outage exposure duration and including missing data. We conducted all simulations using two different study designs to test the consistency of results to different model specifications.

**Exposure and outcome data**

We populated each county with electrical customers, drawn from the empirical distribution of customers served by county in the POUS dataset. To generate hourly counts of customers without power, we drew from the empirical distribution of counts of customers without power in the POUS dataset.

We chose the health-relevant duration of power outage for our study: 8 hours or longer (8+ hours). This was somewhat arbitrary—in a real study, the health-relevant duration would depend on the actual outcome being studied and how power outages were thought to affect that outcome. However, we do hypothesize that 8+ hour power outages matter for electricity-dependent medical device users, as well as heat and cold-driven outcomes caused by outage, so we chose to use 8+ hours in the simulation. We applied our definition of power outage exposure to the simulated exposure data and identified county-days exposed to 8+ hour power outage. This produced a one-year daily time-series of binary power outage exposure data for each county.

We generated outcome data based on these exposure data. We drew hospitalization counts for each county-day based on a Poisson distribution with a base daily hospitalization rate of 0.1%. We increased this hospitalization rate for county-days exposed to 8+ hour outage by 1%, for a total hospitalization rate of 0.101%, based on reported effect sizes in the literature.[[42]](#endnote-42),[[43]](#endnote-43) This produced a one-year time series of daily hospitalization rates for each county. We repeated this procedure twice, in two additional simulations, with base hospitalization rates of 0.1% and rates on exposed days of 0.105% and 0.15%, to test the sensitivity of results to effect size.

**Simulation study design**

First, we used a base case (unbiased) scenario to estimate the true simulated effect of county-day 8+ hour power outage exposure on county-level hospitalization counts. We used a case-crossover design with a conditional Poisson model.[[44]](#endnote-44) Within each county, we chose control days for each day with non-zero hospitalization count (i.e., each case day). We included these case and control days in a conditional Poisson model relating power outage exposure to hospitalization rates. In this model, we included an offset for customers served by county. Again, we repeated this procedure twice, in two additional simulations, with base hospitalization rates of 0.1% and hospitalization rates on exposed days of 0.105% and 0.15%, to test the sensitivity of results to effect size.

We also repeated the simulation using a different study design to test if the simulation results were sensitive to study design. We implemented a study design representing an augmented difference-in-differences design,[[45]](#endnote-45) where multiple counties exposed at different times are each compared to unexposed counties. Because we did not simulate any confounding, we did not choose counties with parallel trends during pretreatment periods, rather, we randomly chose a control county for each exposed county. We used the same exposure and outcome data generated for the case-crossover simulation. For each county-day exposed to a power outage, we chose a control county-day not exposed to a power outage. We ran a conditional Poisson model including these case and control days from all 100 counties. We used exposure and outcome data created 100 times for the case-crossover design to repeat the difference-in-differences analysis 100 times and for effect sizes of 0.5% and 5%.

**Testing wrong assumptions about the health-relevant duration:**

We developed a set of simulations meant to model a researcher making wrong assumptions about the health-relevant duration of power outage. We assessed the magnitude and direction of the resulting bias. These simulations model a case in which the researcher assumed 8+ hour outages caused health effects, but the truly relevant exposure window was actually 4+ hours.

To model this scenario, first, we created an additional power outage exposure dataset for each simulated county. Using the measurement strategy above, we identified county-days exposed to 4+ hour power outages instead of 8+ hour outages. We generated an additional dataset of outcome data, increasing hospitalization rates when counties were exposed to 4+ hour outages. We used the same hospitalization rate of 0.1%, with a 1% rate increase on power outage-exposed days. Then, we mismatched the exposure and outcome data: we paired exposure data indicating when counties were exposed to 8+ hour power outages with outcome data generated based on 4+ hour outages, inducing non-differential exposure misclassification.

We repeated the study we conducted above in the base case/unbiased scenario, using the mismatched datasets. We used a case-crossover design with conditional Poisson models. We chose control days for each day with non-zero hospitalization count. We ran conditional Poisson models to generate effect estimates for the mismatched scenario. We repeated this set of simulations 100 times.

We also repeated this simulation an additional 100 times, substituting 12+ hour power outages for 4+ hour power outages. This created an additional scenario where we misclassified exposure by using 8+ hour power outage exposure data rather than 12+ hour data. Finally, we repeated these simulations for two additional effect sizes, where hospitalization on exposed days were 0.105% and 0.15%.

We repeated the 4+ and 12+ hour simulations using both the case-crossover and the difference-in-differences designs to test whether results were sensitive to the study design in similar analyses as described under the zero-bias scenario.

We calculated bias in all these simulations, using the absolute difference between the estimated and true simulated effects (β\*−β, where β\* is the estimated effect and β is the true simulated effect). We also assessed coverage of confidence intervals in each of the simulations.

**Testing bias due to missing data**

To test bias due to missing exposure data, we created four additional exposure datasets for each of the 100 simulated counties, each with an increasing percentage of missing observations (10%, 30%, 50%, 70%). To create missingness, we randomly removed county-hour observations from the original dataset according to each assumed missingness percentage. We treated missing observations as though they indicated no power outage exposure (0 customers without power) since this is the mean, median, and modal value of customers without power by county-hour in the POUS dataset. We applied our definition of power outage exposure to these four datasets with missingness to create daily binary power outage exposure data based on a power outage duration of 8+ hours.

We then modeled the relationship between 8+ hour power outage exposure measured in the four datasets with missing data (10%, 30%, 50%, 70% missing) and hospitalization counts generated based on an 8+ hour power outage exposure in the complete dataset without missingness. We used both the case-crossover study and the difference-in-differences designs as above. We repeated the simulations 100 times for the main hospitalization effect of 1% and for 0.5% and 5%.

We calculated bias in each of the four cases with increasing missingness using the absolute difference between the estimated effects and simulated effects (β\*−β, where β\* is the estimated effect and β is the simulated effect). We also assessed coverage of confidence intervals.

**Results**

We ran a simulation representing an epidemiological study of power outage and hospitalizations. We created 100 counties populated with electrical customers, and simulated daily power outage exposure for these customers for 1 year. We simulated increased hospitalizations resulting from these power outage exposures. Each simulated county contained an average of Y electrical customers, who experienced a yearly average of X 8+ hour power outages.

With these simulations, we aimed to quantify the bias introduced in this epidemiology study when there was exposure misclassification in power outage exposure, and when there was missing power outage data. We found some evidence of bias in these simulations. On average, results from both exposure misclassification and missing data scenarios were biased downward.

**Health-relevant duration**

In the simulation scenarios representing a researcher making wrong assumptions about the health-relevant duration of power outage, when the health-relevant duration of power outage assumed by the researcher (8+ hours) was longer than the true simulated health-relevant duration (4+ hours), results were slightly biased downward. In this case, the effect estimates returned from the simulation were on average 80% of the true simulated relative risk. The magnitude of bias was the same for all effect sizes and study designs.

However, when the health-relevant duration of outage assumed by the researcher (8+ hours) was *shorter* than the true simulated duration (12+ hours), results were substantially biased downward. In this case, effect estimates returned by the simulation were on average 50% of the true simulated relative risk—the largest bias of all the simulation cases. Again, magnitude of bias was the same for all effect sizes and study designs.

In scenarios modelling incorrect assumptions about the health-relevant duration, coverage varied widely by effect size and was different between the two exposure misclassification scenarios. In all scenarios, the expected coverage of 95% confidence intervals was 95%. In the simulation case where 4+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models with simulated effect size 0.05% was close to 100%. For effect size of 5%, coverage was close to 65%.

In the second health-relevant duration simulation, when 12+ hour power outages caused increased hospitalization risk, but the researcher assumed it was 8+ hour outages that caused health effects, coverage for models with simulated effect size 0.05% was close to 80%. However, for the effect size of 5%, coverage was 0%.

**Missing data:**

In those simulations where missing data were introduced, as more data were missing, the estimated relative risk was biased further towards the null. At 10% of data missing, effect estimates returned from the simulation were 90% of the true simulated relative risk. When 50% of data were missing, effect estimates returned from the simulation were 75% of the true simulated relative risk, and when 70% of data were missing, effect estimates were 50% of the true simulated effect. The magnitude of bias was not sensitive to study design or effect size.

In these scenarios, coverage was high when effect sizes were small. When 10% of data were missing and the effect size was 0.05%, coverage was >95%. Coverage dropped substantially in all cases as effect size increased. When 10% of data were missing and effect size was 5%, even though results were minimally biased, coverage was about 30%.

Coverage in missing data scenarios also decreased as the proportion of missing data increased. Coverage was about 0% when 50% or 70% of data were missing and effect size was 5%. Overall, in exposure misclassification scenarios and missing data scenarios, coverage was slightly lower when using a case-crossover design.

In summary, the largest bias was introduced from wrong assumptions about health-relevant duration of power outage. There was also substantial bias when 50%-70% of data were missing. Results from other simulation scenarios were minimally biased (Table 1, Figure 2).

**Discussion:**

We developed a strategy to define and measure power outage exposure to support epidemiologic research. We measured bias from misidentifying the health-relevant length of power outage and missing data in simulations. Our measurement strategy and simulation results will allow researchers to use available datasets to consistently measure power outage exposure while minimizing potential bias in future epidemiological studies. Based on our results, we recommend that researchers avoid underestimating the health-relevant duration of power outage, as this can introduce substantial bias. We also recommend researchers exclude spatial units missing more than 50% of exposure information from analyses.

We found evidence of bias in simulations where we modeled incorrect assumptions about the health-relevant duration of power outage and where we modelled missing data. Results were the most biased in those simulations representing a researcher making wrong assumptions about the health-relevant duration of power outage. Bias was largest when researchers assumed that the health-relevant duration of power outage was shorter (8+ hours) than the true simulated health-relevant duration (12+ hours). However, when the researcher assumed that the health-relevant duration of outages was longer (8+ hours) than the true health-relevant duration (4+ hours), there was minimal bias. When large proportions of exposure data were missing (50-70% missing), there was substantial bias, but results were minimally biased in scenarios with fewer missing data (10-30% missing). The magnitude of bias did not depend on study design or effect size. However, coverage was low when the simulated effect size was larger and effect estimates were substantially biased, since results were more precise than in simulations with smaller effect sizes.

All studies using the NYS power outage dataset have used similar (but not identical) definitions of power outage exposure to the one we propose here, including Northrop et al. 2024[[46]](#endnote-46). These studies have all used a cut point-based definition where spatial units are exposed to power outage when >*k*% of customers are without power, though details about the duration of power outage or the cut point have varied. Northrop et al. assumed that the health-relevant duration of power outage for unintentional pediatric injury hospitalizations was 4+ hours. According to our results, if longer duration outages were actually more relevant, effect estimates in Northrop et al. could be biased substantially downward. If slightly shorter outages were actually relevant, which could be possible since injuries might be related to darkness or increased candle or natural gas use, the original results could be slightly biased downward. Finally, if spatial units in the NYS dataset used in Northrop et al. had substantial missing data, effect estimates may have been biased towards the null.

If researchers are unsure of the health relevant duration of power outage for their outcome, we recommend conducting sensitivity analyses varying the health-relevant duration or using a continuous measure of the daily number of hours without power to identify the health-relevant duration of outage. Researchers should avoid underestimating the health-relevant duration, as this could result in substantial bias.

To minimize bias from missing data, which our results show can introduce substantial bias, researchers may exclude counties with high percentages of missing data (50% of customer-time missing). However, ignoring missing data or excluding counties with high percentages of missing data could result in selection bias or affect generalizability. We suggest that researches do exclude spatial units missing more than 50% of person-hours of power outage data from analyses, as these levels of missing data do substantially bias results, but we also suggest that researchers carefully compare characteristics of included vs. excluded counties to assess generalizability, and interpret any results accordingly. Researchers could also conduct sensitivity analyses, where they compare results from models including only counties high person-coverage (for example, >80% of data present), to results including all counties.

**Limitations**

First, in this study, we only assessed bias from random missingness. In the POUS dataset, data may not be missing at random. Anecdotally, we have noticed some utility company websites are unavailable during large outages, suggesting that data could be missing more often from the POUS dataset during large outage events. We did not examine bias from non-random missingness, and bias could be substantial in either direction. Future research should explore this possibility in order to provide improved recommendations for handling missing power outage data.

Second, studies using existing datasets measuring power outage exposure need to use aggregate, spatial unit measures of power outage to estimate effects, as there are no large-scale individual-level power outage datasets available. We did not assess how aggregating measurements from the individual level to spatial unit level could bias effect estimates. Future studies are needed to address this question.

Third, we opted to construct a binary power outage exposure variable. This construct captures the two dimensions of power outage exposure (magnitude and duration), and aligns with how many people think about power outages, making it easily interpretable and policy-relevant. For some questions, a continuous measure of power outage exposure in a spatial unit (i.e., number of hours of power outage) might make more sense. Specifically, when there is no prior hypothesis on the health-relevant exposure duration, use of a continuous exposure (i.e., hours out) could facilitate identification of a potential threshold point. Researchers will need to select the best definition of power outage for their particular research question.

**Conclusion:**

Currently, power outage is understudied exposure, but power outages are increasing in frequency and duration with climate change. Researchers and the public are recognizing the importance of power reliability and the health consequences of outages, especially for vulnerable populations such as children, older adults, and people who rely on life-sustaining electricity-dependent medical equipment. When outages are caused by climate-driven severe weather events, such as extreme heat or cyclones, health risks may be even greater[[47]](#endnote-47),[[48]](#endnote-48).

To date, data availability has constrained research on power outages and health. We developed a new national dataset of power outage exposure, the POUS dataset, which could expand the study of power outage and health outcomes. Because there is substantial missing data in the POUS dataset, and no established method to measure power outage exposure in the literature, we developed a strategy to measure power outage exposure. Then, we used simulations to test how much incorrect assumptions about health-relevant duration of power outage and missing data could bias the results of epidemiological studies of power outage and health outcomes.We found that there was substantial bias introduced in some cases, when the health-relevant duration of outage was assumed to be shorter than the true, and when more than 50% of exposure information was missing in a county. Our results show that while bias is likely, sensitivity analyses and careful choices of health-relevant duration can help researchers describe the range of plausible effect estimates in epidemiological studies of power outage and health.

Despite the high percentage of missing data in the POUS dataset, the dataset is still high resolution, with hourly measurements in 2,447 US counties over 3 years. Even after excluding counties missing >50% of exposure data, the dataset covers ~70% of the US population. We hope researchers can use our results to define and measure power outage exposure in future epidemiological studies based on the POUS and NYS datasets available, while minimizing potential bias.

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