**Measuring power outage exposure with simulations**

**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 increase accidents and injuries related to generator and natural gas use[[11]](#endnote-11),[[12]](#endnote-12). 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, and other adverse cardiorespiratory outcomes following such exposures[[13]](#endnote-13),[[14]](#endnote-14),[[15]](#endnote-15),[[16]](#endnote-16).

Despite the health risks of power outages, data describing power outage exposure are extremely limited[[17]](#endnote-17),[[18]](#endnote-18), constraining research. To our knowledge, only one US-based dataset describes outage exposure across space and time[[19]](#endnote-19) at a sub-county spatial scale, covering only New York State. This dataset has allowed for evaluation of the impact of power outages on health[[20]](#endnote-20),[[21]](#endnote-21),[[22]](#endnote-22),[[23]](#endnote-23),[[24]](#endnote-24). However, almost all published studies of power outages to date rely on this single dataset[[25]](#endnote-25), meaning any 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 disasters that disrupted power as a surrogate for the timing of power outage exposure in specific locations[[26]](#endnote-26),[[27]](#endnote-27). These studies consider everyone in a city or county exposed to the power outage in 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 power outages and health.

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 may improve community health. Knowing the health risks of power outages can also motivate interventions in vulnerable populations to prevent adverse health outcomes[[28]](#endnote-28).

In our previous work, we created a new national dataset of hourly power outage exposure by county in the continental United States[[29]](#endnote-29) (the PowerOutages.us dataset, or POUS dataset). This dataset will allow us 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 power outage exposure assessment remain. First, there is no established strategy to measure health-relevant power outage exposure in the literature[[30]](#endnote-30). 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. 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 some duration may cause 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[[31]](#endnote-31),[[32]](#endnote-32), 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). In these cases, imputing missing values is nearly impossible because no data exist from which to draw information. To reduce exposure misclassification among study counties, researchers could exclude counties that are missing more than a specified percentage of observations from epidemiological studies. However, removing too much data could threaten the generalizability of effect estimates from these 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 actually the correct exposure duration. To deal with missing data, we used simulations to identify a percentage cut-point, above which if a county had more missingness, the missing data began to severely bias outage-health effect estimates. We tested the sensitivity of simulation results to effect size and study design.

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.

**Methods:**

**Power outage data structure**

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[[33]](#endnote-33) (the POUS dataset). Most utility websites report the number of customers without power by neighbourhood or city in real-time. PowerOutages.us leveraged 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[[34]](#endnote-34). We used this compilation to produce the POUS dataset.

The POUS dataset contained hourly counts of customers without power for US counties (n = 2,447) 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[[35]](#endnote-35). 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, 20 customers were out for 1 hour each.

The New York State power outage dataset (NYS dataset) is structured similarly – counts of customers without power are reported by hour by power operating division[[36]](#endnote-36),[[37]](#endnote-37). 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**

We developed the following strategy to measure daily power outage exposure in the POUS dataset and New York State dataset.

At the individual level, power outage exposure is binary: electricity is either on or off at a person’s residence. However, the only data available to measure power outage are at the spatial unit level, as counts of customers out, which are continuous and can be interpreted in multiple ways. Since the health-relevant duration of power outage may change depending on the health outcome studied, we developed a flexible definition of power outage exposure to identify power outages of varying lengths. Our definition can be used to identify binary daily power outage exposure, or characterize the number of hours without power by day and spatial unit. We conducted these simulations using a binary definition of power outage exposure since we BLANK

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 the 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 *L* (for example, *L* = 8 hours). *L* 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 ‘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%[[38]](#endnote-38). 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.

We propose using the binary 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 was meant to mimic a study that could be conducted using the POUS data. The outcome of ‘hospitalizations’ is intentionally vague and could be any health outcome hypothesized to be 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 sensitivity of results.

**Exposure and outcome data**

We generated one year of county-hour power outage exposure data for 100 simulated counties. 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[[39]](#endnote-39),[[40]](#endnote-40). This produced 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 hospitalization 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 quasi-Poisson model[[41]](#endnote-41). 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 quasi-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, where multiple regions exposed at different times are each compared to unexposed regions. Because we did not simulate any confounding, we did not choose regions with parallel trends during pretreatment periods, rather, we randomly chose a control region for each exposed region. 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 Poisson model including all 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 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 quasi-Poisson models. We chose control days for each day with non-zero hospitalization count. We ran quasi-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 effects 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 found some evidence of bias in these simulations representing an epidemiological study of power outage and hospitalizations, in cases modelling exposure misclassification and missing data. On average, results from these cases were biased downward.

**Health-relevant duration:**

In the simulation cases 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 shorter than the true simulated health-relevant duration (12+ hours), results were substantially biased downward. In this case, the effect estimates returned from the simulation were on average 50% smaller than the true simulated relative risk – the largest bias of all the simulation cases. 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 *longer* than the true simulated duration (4+ hours), results were slightly biased downward. In this case, effect estimates returned by the simulation were on average 80% of the true simulated relative risk. Again, magnitude of bias was the same for all effect sizes and study designs.

In scenarios modelling incorrect assumptions about health relevant duration, coverage varied widely by effect size, and was different between the two exposure misclassification scenarios. 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, because bias was minimal and effect estimates imprecise. For effect size of 5%, coverage was close to 65%. Coverage was lower because of increased precision.

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%. Even though these effect estimates were biased, they were imprecise due to the tiny effect size, leading to higher coverage. However, for the effect size of 5%, coverage was 0%, since effect estimates were both substantially biased and precise.

**Missing data:**

In simulation cases where missing data were introduced, as more data were missing, the relative risk returned from simulations was biased further towards the null, as expected. 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 scenarios with missing data, coverage was high when effect sizes were small, even if there were large amounts of missing data. When 10% of data were missing and the effect size was 0.05%, coverage was >95%, due to effect estimate imprecision. Coverage dropped substantially in all cases as effect size increased, due to the increased precision of results. 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, due increased bias in effect estimates. 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, since results from this design were slightly more precise.

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. Other simulation cases were minimally biased (Table 1, Figure 2).

**Discussion:**

We developed a strategy to consistently define and measure power outage exposure. 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.

In simulations where we modeled incorrect assumptions about the health-relevant duration of power outage, and exposure data missing substantial percentages of observations, we found evidence of bias. Results were the most biased in the simulation cases representing a researcher making wrong assumptions about the health-relevant duration of power outage, 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 (30-50% missing). The magnitude of bias did not appear to depend on study design or effect size. However, coverage was low in cases with a larger effect size where the effect estimates were substantially biased, since results were more precise than cases with smaller effect sizes.

All studies using the New York State dataset have used similar (but not identical) definitions of power outage exposure to the one we propose here, including Northrop et al. 2024[[42]](#endnote-42). 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 or 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 natural gas use, results could be slightly biased downward. Finally, if spatial units in the New York State dataset used in Northrop et al. were missing substantial 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 results in substantial bias.

* Our results show that spatial units with >50% missing data could help reduce bias in any future studies using power outage data, as effect estimates from simulations with fewer missing data were only slightly biased, whereas the magnitude of the bias increased substantially after 50% of observations were removed from the dataset.

Currently, power outage is an understudied exposure, but researchers and the public are recognizing the importance of power reliability and the health consequences of outages. When outages are caused by climate-driven severe weather events, such as extreme heat or cyclones, health risks may be even greater. To date, data availability has constrained research on power outages and health. The POUS dataset could expand the study of power outage and health outcomes. Wrong assumptions about the health-relevant length of power outage and missing data may bias results of studies using this dataset. Our results show that bias is possible, but sensitivity analyses and careful choices of health-relevant duration can help researchers avoid incorrect effect estimates. 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.

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.

Second, studies using existing datasets measuring power outage exposure will use aggregate, spatial unit measures of power outage to estimate effects, as there are no 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.

**Conclusion:**

Because there is only a single dataset describing power outage exposure at the spatial unit level, we developed a new national dataset of power outage exposure, the POUS dataset. Even with these new data, major challenges with power outage exposure assessment remained.We proposed a consistent definition for measuring power outage.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 more than 50% of observations were missing in a county, and when the health-relevant duration of outage was assumed to be shorter than was true.We suggest conducting sensitivity analyses on health relevant duration of power outage to address this bias, and BLANK REC FOR MISSING DATA. We hope researchers can use our results to consistently define and measure power outage exposure in future epidemiological studies based on the datasets available, while minimizing potential bias.

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