Intro:

Power outages are becoming much more common. As climate change increases the frequency and intensity of extreme heat events, wildfires, hurricanes, and other severe weather, the US electrical grid is aging. On average, electrical customers experienced 8 hours without power in 2020, the longest duration on record.

Power outages have substantial health effects in vulnerable populations such as older adults, people who use life-sustaining electricity-dependent medical equipment, and children. Loss of electricity can be life-threatening for people electricity-dependent medical equipment such as at-home ventilators or oxygen tanks. Older adults may be susceptible to cardiorespiratory disease-related health effects from heat or cold exposure, when heating and air conditioning is unavailable during power outages. Outages increase pediatric injuries, because of accidents related to increased generator and natural gas use. They also increase pediatric asthma emergencies, because power outages increase heat and humidity exposure when air conditioning is unavailable.

Despite the health risks of power outage, especially to vulnerable populations, data describing power outage exposure is extremely limited. Only one dataset in New York state describes outage exposure across space and time. Other studies of power outage have relied on on large-scale events (e.g., hurricanes) as a surrogate of outages across a broad area (e.g., an entire city) at a specific time (e.g., August 2003)*.* These studies cannot disentangle health effects from disaster exposure and power outage exposure, or estimate exposure-response relationships.

In our previous work, we created a new national dataset of 10-minute resolution power outage exposure in sub-county spatial units for the continental United States. We used this dataset to describe power outage exposure by region and social vulnerability. This dataset will allow us and other researchers to describe exposure-response relationships between power outage and health outcomes.

However, there are still major challenges with exposure assessment using available power outage data. First, there is no standard definition of power outage exposure in the literature, which would allow comparison and aggregation of study results. There is also no literature on the clinically relevant length of power outage. In order to conduct an epidemiological study of power outage exposure using these newly available data, we need to define and quantify power outage. Any definition of power outage exposure would depend on the clinically relevant length of outage exposure. An incorrect assumption about the clinically relevant length of power outage could substantially bias the results of an epidemiological study. Second, both the national dataset we developed and the New York State dataset are missing large amounts of data. This missingness could also substantially bias results of an epidemiological study of power outage and any health outcome.

We hypothesize that

assessing power outage exposure using these data is still challenging.

* Power outage important exposure because of effects on vulnerable populations such as older adults, DME users, and children
  + Can be threatening w DME users
  + Can lead to cardiorespiratory problems in older adults from heat, cold, or lack of access to healthcare
  + Can lead to injuries in kids
* Becoming much more common
  + climate change is causing increases in heat, wildfires, and extreme weather, all causes of outages
  + US electrical grid is aging
  + People experienced longest number of hrs out yet in 2020
* Data on power outages is extremely limited
  + Only one dataset in New York state describing magnitude of outage exposure by neighborhood over time
  + All other literature looks at disaster/extreme weather event as proxy for outage
  + Doesn’t allow you to determine exposure-response relationship
* We have a new national dataset of 10-minute resolution power outage exposure in sub-county spatial units for the whole US.
  + Will allow us to look at exposure-response for outcomes like hospitalizations in older adults or people who use DME
* But, there are still challenges with exposure assessment
* Clinically relevant power outage:
  + Because it’s such a new exposure, there is no agreed upon definition of power outage in the literature, so we need to come up with one
  + But, we don’t know how long clinically relevant power outages are
  + Could be 8 hours because of DME and heat, but could also be longer or shorter
  + Will vary for different outcomes and by person
  + But regardless, we need to define clinically relevant power outage exposure at the county level, which is also slightly different from individual clinical relevance
* Missing data:
  + There’s also still a lot of missing data in our dataset
  + Need to figure out how much missing data could bias the results of an epidemiological study of power outages
  + Want to know when to include/exclude counties from analyses based on % of data missing
* We’ll address these challenges with exposure assessment in this paper by running simulations
  + These simulations will help us define power outage and deal with missing data
  + We’ll see how biased we are if we don’t identify the length of clinically relevant power outage at the county level properly and in which direction that bias may be
  + We’ll see how much data needs to be missing in order for us to get biased effect estimates/when we should throw counties out of our analysis
  + Other epidemiologists may also want to conduct similar simulations when dealing with similar exposure assessment problems, or novel exposures, so we hope this paper can be an example of how to carry out such a simulation
  + Data on lead paint, radon exposure, or drinking water contamination follow a similar structure
    - inherent exposure misclassification bc every unit is either exposed or unexposed but you’re summarizing
    - have to decide on summary measures and test how they will work/if they’ll cause bias
    - also may be missing chunks of data in space or time
    - simulation tests that

Methods:

Data structure:

We purchased raw power outage data covering the continental US for the years 2018-2020 from poweroutages.us. These data came from the public websites maintained by utility companies, designed to be used by a utility’s customers to check if there is a power outage in their area. Poweroutages.us scraped counts of customers without power from these websites in real time, every ten minutes, from 2018-2020. The resulting data contains 10-minute resolution counts of customers without power all served by the same utility in a sub-county unit. Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business. A sub-county unit can be an entire county, city (where there are possibly multiple cities in a county), or neighbourhood (where there are possibly multiple neighbourhoods in a city, in turn nested in a county). All sub-county units were nested inside counties. Many utilities can serve the same location, so these sub-county units were not necessarily geographically distinct. Two houses next to each other might be in two different spatial units in the power outage data if they were served by different utilities.

The sub-county unit level data is time series of ten-minute intervals covering 3 years, where there is an estimate of the number of customers without power in a sub-county unit in every 10 minute interval. The counts of customers out do not necessarily track the same customers: if 10 people are reported without power in two subsequent 10-minute periods in a subcounty unit, the data do not contain information about whether the same 10 households were out. The data only show that 10 households were out in each interval.

Because all subcounty units were nested inside counties, we were able to aggregate 10-minute counts of customers without power to the county level. We also aggregated these counts to the hourly level.

Simulation: clinically relevant length of power outage

* don’t know how long the power has to be out at the individual or county level for there to be health effects
* want to run a simulation to see if we guess wrong, how much bias this would introduce in a study
* other studies have defined binary power outage exposure over a spatial unit (whether there was an outage, Y/N) by considering an outage on if the percentage of customers without power in a spatial unit exceeds a threshold
* can do this with multiple thresholds
* Northrop et al: three thresholds of 10%, 20%, and 30%
* Allows you to look for a relationship between the ‘strength’ (how many people are correctly identified as experiencing an outage/extent of exposure misclassification) of outage and health outcome
* But, you still need to define a length of outage – does a ten minute outage count as significant for health?
* We’re looking to mark days as exposed or unexposed to outage, so want to decide on a length of time that the number of customers have to be above the threshold for a county to be exposed?
* Initially hypothesized that 8 hrs is relevant for cardiorespiratory effects because of DME and temperature at the individual level
* But no studies have looked at this and there’s no evidence
* Also no evidence for county-level exposure thresholds – like, 8 hrs of county outage isn’t the same and we still need to determine that
* So, we were concerned that if it was in fact shorter or longer outages that mattered for health, we could get really biased results in our study if we cleaned the data and marked days as exposed or unexposed based on 8 hour outages. Said differently, if it was instead 4 hour outages or 12 or outages that were clinically relevant and mattered for health, and we cleaned the data as if it were 8 hour outages that mattered, we would be introducing serious exposure misclassification.
* Want to run a simulation testing how much bias

How we did the simulation:

Data preparation:

* Simulated 100 counties
* Assigned each county sub-county areas based on empirical distribution of the number of subcounty areas
* Populated each subcounty area with simulated customers based on the empirical distribution of customers in subcounty areas
* Generated 10-minute counts of proportion of customers out in each sub-county area for 1 year.
  + Drawn from empirical distribution of proportion of 10-minute counts of customers out in the real poweroutages.us data
  + Used proportion of customers out because subcounty areas had very different denominators/numbers of customers served
  + Turned these into 10-minute counts of customers out
* Aggregated these sub-county 10-minute counts of customers without power
  + Aggregated counts to the county level by summing the number of customers in all sub-county areas in each ten minute period to get 10-minute county-level counts of customers out
  + Took the average customers out in each county in each hour to get hourly county-level counts of customers out
* We used a “0.5% out” definition to develop a county time series of hours exposed to power outage based on hourly-county counts of customers without power. We marked a county-hour exposed if the percentage of customers without power in county *i* during hour *j* exceeded 0.5% of the customers served in county *i*. Finally, we aggregated to the daily level: we considered a county-day as exposed if there were 8 consecutive hours of ‘power outage on’ (customers without power percentages > 0.5% of county) in that county on that day. Power outages could last more than 24 hours. We also considered a county-day as exposed if a power outages lasting longer than 8 hours ended on that county-day. This left us with a one-year time series indicating if there was a power outage on each day in each of the 100 simulated counties.
* This gave us a time series of binary power outage exposure (y/n) for 1 year for 100 counties, with denominators indicating the population of each of these counties (the number of customers served).

Simulation set up:

* First, we simulated an unbiased scenario where exposure was defined correctly, and there was no exposure misclassification based on the length of clinically relevant power outage
* Generated simulated outcome data for a hypothetical epidemiological study looking at power outage exposure and hospitalization rates, as a few have done (cite alex and dominianni)
* We generated daily hospitalization data for each of our 100 simulated counties for 1 year. We drew hospitalization counts for each county-day based on the total number of customers living in a county, from a Poisson distribution with a base rate of 0.1%.
* County-days that met the 8-hour outage definition received a 1% rate increase (for a total hospitalization rate of 0.101%).
* To generate an estimate for the effect of an 8-hour power outage on daily county-level hospitalization counts, for each day exposed in a county, we chose control days that were within 3 weeks of the exposed day, matching on the day of week and month.
* This matching is close to what would be used in an augmented difference-in-differences design that could be used to compare hospitalization rates in counties exposed to power outages with those not exposed. Because there is no confounding in the simulation, we don’t really have to pick these days carefully at all,

We used these case and control dates in Poisson models.

* We used one Poisson model per county (for a total of 100 models) to model the relationship between the binary 8-hour power outage exposure and daily hospitalization counts, with an offset for the number of customers in a county. These models represented an unbiased scenario where exposure was defined correctly – 8 hr exposure caused an increase in hospitalizations, and this was reflected correctly in the simulation.

Testing bias from exposure misclassification related to the length of clinically relevant outage:

There is no literature on the clinically relevant length of a power outage, so we do not know how long a power outage must last to cause health effects. This also depends on the study population and health outcome in question. For vulnerable older adults who use electricity-dependent medical equipment, we hypothesize that the clinically relevant length of a power outage is around 8 hours for cardiorespiratory-related hospitalizations. In this simulation, we aim to test how incorrect assumptions about the clinically relevant length of power outage could bias the results of an epidemiological study of the health effects of power outage. It’s possible that 12-hour or 4-hour power outages could cause hospitalizations among older adults who use DME. If 12-hour or 4-hour outages are causing hospitalizations, but we incorrectly assume that 8-hour power outages cause hospitalizations, what bias would this create? We aim to estimate how much this type of exposure misclassification could bias effect estimates of an epidemiological study of power outages and a hypothetical health outcome of hospitalization.

Here, we set up a simulation representing an epidemiological study where we are measuring daily power outage in 100 US counties, county-level hospitalization rates over 1 year, and estimating the effect of power outage exposure on county-level hospitalization rates.

We set this simulation up similarly to the base case above.

In this simulation, we aim to test by how much it will bias our results if we make incorrect assumptions about the clinically relevant length of power outage.

* Want to test how much it would bias our results if we were wrong about the length of clinically relevant outage
* we don’t know how long clinically relevant power outages are
* if 12-hour outages cause effects, but outages shorter don’t do anything, but we incorrectly assume that 8-hour outages cause effects, and classify days with 8-hour outages as exposed, how much would this bias our results?
* We are testing this in this simulation
* To do this, we created two additional exposure datasets for each county, defining a county-day as exposed if there was either a 4-hour outage (customers without power counts > 0.5% of total customers for 4 consecutive hours) or a 12-hour outage (defined the same but for 12 hours).
* Again, we generated daily hospitalization data for each of our 100 simulated counties for 1 year, and created two datasets using each of the two exposure datasets. As before, we drew hospitalization counts for each county-day based on the total number of customers living in a county, from a Poisson distribution with a base rate of 0.1%.
* However, this time, in our first dataset county-days that met the a 4-hour power outage definition and were marked as exposed in the 4-hour dataset received a 1% rate increase (for a total hospitalization rate of 0.101%). In the second dataset, county-days that met a 12-hour outage definition received a 1% rate increase.