Intro: why does measuring power outage matter? And how and when does it need to be measured?

Power outages increasing w climate change:

* Power outage incidence increasing
* Severe weather main cause of power outages and increasing due to climate change
* Grid is aging and has not been updated to withstand current climate-driven severe weather
* Therefore power outage incidence is the worst it has ever been

Power outages are a health risk:

* Health risk for vulnerable pops even if not a risk for most people
* Can affect a wide variety of health outcomes
* Older adults, children, DME users, at risk
* CVD and respiratory disease assoc w outage in older adults, maybe bc of heat/humidity or cold, esp in severe-weather driven outages
* DME users devices directly affected, life threatening
* Children at risk of accidents from generator and natural gas use, and asthma exacerbations due to heat and humidity

Power outage is an understudied exposure. Research is really limited because there isn’t good data.

* Most epidemiological studies from NYS dataset; no other datasets
* Only dataset to measure outage across time and space
* Other studies use disasters are surrogate for exposure
* Can’t estimate exposure-response relationships from studies like that or disentangle effects of power outage from disaster
* To justify intervention to prevent possible accidents and asthma in children, CVD, protect DME users, need to quantify risks by estimating exposure-response relationships btw outage and health outcomes, beyond NYS and in potentially vulnerable pops. Could vary by region, cause of outage, co-occurring hazards
* Need data to do that.

We created a dataset to enable this research

* 10 min subcounty level national data 2017-2020, plan to update to later years
* Can help us answer questions about health risks of power outages
* We characterized power outage frequency and how often it co-occurred with social vulnerability, which increases risk of all kinds of health effects of power outage national
* Showed outages most common in SE and co-occur w high SVI there

However, still major exposure measurement challenges even with this new data.

* No standardized strategy to measure outage in literature bc so few studies examine outage
* Need a strategy that minimizes potential measurement error, and can be used to ensure comparability and aggregation between studies
* Also issues with two potential sources of bias. don’t know about health-relevant length, no research on health relevant length and any outcome
* all datasets contain a lot of missing data
* Both those things can bias study results

Here we develop a power outage measurement strategy we think people can use.

* Then, run simulations to test how much wrong assumptions about health-relevant length can bias
* Also test how much missing data could bias
* Our results will allow us and other researchers to consistently define and measure power outage exposure using the datasets currently available, including the new national dataset we developed and the new national dataset, while minimizing potential bias in future epidemiological studies of power outages and health outcomes.

Methods:

What is power outage data like?

* Bought from poweroutages.us, which scrapes utility company sites APIs in real time to determine numbers of customers without power, designed for customers to be able to check if power is on or not
* Covers US 2017-2020, updating data for more recent years.
* Time series of 10-minute intervals of customers without power in a utility by ‘subcounty unit’ for entire US over time period
* Utilities define a ‘customer’ as a grid connection, which can correspond to a household, apartment building, or business
* ‘subcounty unit’ is 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)
* 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.
* New York state data is structured similarly except for no geographical overlap
* We aggregated data to achieve county-hour counts of customers without power by summing all customers out in a county in each ten-minute period and then averaging those counts over each hour.
* Achieved no geographical overlap and smoothed data to hourly level.

How will we measure power outage?

* Interested in binary exposure bc we think this is most interpretable from a policy perspective.
* Could use percentage of customers without power and relate increases in customres without power to health outcomes, but not very interpretable to policy makers trying to respond in large outage scenarios.
* Also need a definition that captures duration. For some health outcomes there is a health-relevant duration – ex DME
* Want to be able to capture that.
* To achieve something interpretable that measures duration,
* Previous literature has used cut-point based definition to measure when an area is experiencing a ‘power outage’, or a substantial number of people compared to the population are without power.
* In a certain hour, if more than i% of customers are without power in county j, then that county is experiencing a power outage in that hour.
* If power is out for more than x+ consecutive hours ending in a 24-hour period, then on that day the county is experiencing a ‘x+ hour power outage’),
* We think this is a useful definition and propose to use it because because:
  + Can choose a health relevant duration and measure that
    - Will mean mnay people will be without power for that amt of time in spatial unit
    - But not everyone
* This definition does include exposure misclassification
  + - If you mark people based on 30% threshold, many will actually have power when you mark a certain hour as exposed
    - Can vary threshold to do a sensitivity analysis on this, which is useful
    - Solves that problem.
* Percentages allow us to compare counties/spatial units with different populations
* We propose therefore using this definition and doing sensitivity analyses like this one to measure binary power outage.
* Additionally – can use this to have a continuous metric as well that could be useful for outcomes where you don’t’ need or want a binary metric
  + Can use to have continuous but interpretable metric of number of hours that a county has had without power, by summing number of hours where customers out exceeds threshold. Can look at max number of hours without power, total number of hours, total consecutive – useful for different health outcomes
  + Maybe useful for asthma or for anxiety or to measure reliability
  + We won’t go super in depth here about the possibilities with this conituous measure bc we’re most interested in binary in this paper

Simulations:

Even with this measurement strategy for power outage, issues with health relevant length and missing data could bias results of epidemiological study:

Using this strategy still an issue w health-relevant length:

* May want to determine binary exposure to an outage of a certain length to measure something like health effects on DME users
* However don’t know what health-relevant length is for any outcomes
* No literature on topic
* If you pick one like 8 hours, could be wrong about the health relevant length, you’d be introducing exposure misclassification
* Making a really strong assumption w no information
* But if you’re interested in duration you need to pick a length
* what can we do about this?
* Simulation to test how picking the wrong length would bias results and in what direction

Also have issue with missing data

* some data missing in time series
* some counties missing coverage from certain utilities
* counts are underestimates of total counts of customers out
* could bias results of a study
* how bad is this? Is the dataset still usable? Would we be able to get effect estimates from these data?
* Simulation to test how much missing data messes up results.

Simulations:

Set up:

* Designed a simulation representing a study of power outage exposure and some hypothetical outcome (call it hospitalizations) but could be any outcome
* Simulated power outage exposure data for 100 counties for 1 year, made to look like data from real poweroutages.us dataset (drawn from empirical distribution of power outage data counts, and then aggregated etc. )
* Want to measure daily binary power outage exposure to 8+ hour outages bc we think that’s health-relevant length
* Also simulated daily county-level hospitalization rates are also measured over 1 year, and the study aims to estimate the effect of county-level binary power outage exposure on county-level hospitalization rates using a difference-in differences study design.
* Want to use this setup to see how wrong assumptions about health-relevant length and missing data influence results.

Health-relevant length:

* Applied definition of power outage exposure described above to data for 100 counties for 1 year to determine binary exposure based on 8+ hour power outages
* Did this again to determine exposure to 4+ and 12+ hour power outages
* Simulated outcome data based on a 1% increase in hospitalization rate w power outage
* Paired outcome data generated based on outcome inc with 4+ and 12+ hour power outages w 8+ hour exposure data
* Calculated effect estimate for increase based on wrong health-relevant assumption

Missing data:

* To model missing exposure data, we created four additional exposure datasets for each of the 100 counties, each with an increasing percentage of missing observations (10%, 30%, 50%, 70%). To create missingness, before aggregating exposure datasets from the 10-minute subcounty level, we randomly removed 10-minute sub-county level observations from the original dataset until the correct percentage of observations were gone. We then aggregated these four datasets to the county-day level as above, treating missing observations as if they indicated no power outage exposure.
* We then modeled the relationship between exposure in each of the four datasets with missing data (10% - 70% missing data) and all-cause hospitalization counts generated based on a complete dataset in each of the 100 counties. We chose exposed and control days as we did for the ground truth scenario. We used four Poisson models per county (one each for 10%, 30%, 50%, and 70% missingness respectively for a total of 100 models per dataset) to model the relationship between the binary 8+ hour power outage exposure based on the datasets with increasing missingness, and daily hospitalization counts based on the complete 8+ hour exposure data, again with an offset for the number of customers in a county.
* We calculated bias due to missing data for each of the four cases using the absolute difference between the estimated effects and simulated effects in each of the 100 models (*𝑙𝑛*(*𝛽*ˆ)−*𝑙𝑛*(*𝛽*); *𝛽*ˆ is the estimated effect and *𝛽* is the simulated effect). As in the previous simulation, we also calculated coverage – the proportion of simulations where the 95% confidence intervals included the simulated effect (Figure 2).

Simulation Results: