Tropical Storm Paper

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Statement of key issue

Extensive physical exposure data is often available for tropical cyclones as they near and cross communities in the United States. This data can come both from established monitoring networks, like [NOAA network name?], but also may result from data collection efforts during or after the storm by atmospheric scientists and engineers seeking to characterize a specific storm.

Researchers in a variety of fields—including epidemiology, economics, and social sciences—are interested in how these severe storms impact humans. However, while there is often a wealth of physical exposure data collected for a storm, it is not always straightforward to integrate these physical exposure measurements with data characterizing human impacts. A particular challenge is that the resolution of physical exposure and human impact datasets—both in terms of spatial resolution and temporal resolution—often differ for measurements of outcomes among humans compared to the resolutions typically used in measuring physical exposure data.

In this paper, we will provide examples of how tropical cyclone exposure data can be misaligned, or require aggregation, both spatially and temporally to allow them to be integrated with data characterizing human impacts of the storm. Further, we will go through several common temporal and spatial resolutions in which outcome data from past studies of the human outcomes of tropical cyclones in the United States have been available. We will discuss how differences in resolution between exposure and outcome datasets can create challenges in measuring and inferring the association between tropical cyclone exposure and human impacts, including potential biases and reduced precision in estimates of these associations. We will finish by discussing tools and challenges in integrating exposure and outcome datasets in the face of these differences in resolution in the original data and paths forward in resolving these challenges.

Implications of not improving this integration

Differences in resolution between exposure and outcome datasets can create challenges in measuring and inferring the association between tropical cyclone exposure and human impacts. When studying the economic, social, and health impacts that tropical storms and hurricanes have in places such as the Gulf Coast of the United States, it is important to select an appropriate spatial and temporal scale in order to adequately classify exposure. Mis-matches in the spatial and temporal scale of exposure data versus outcome data can create challenges when measuring and inferring associations between tropical cyclone exposures and human impacts. Two potential implications are that this mis-match can introducing bias in estimated associations and that it can reduce precision in estimates of those associations.

Misclassification error / measurement error. One pathway for problems is through misclassification / measurement error bias. Misclassification error occurs when exposure and outcome variables are measured in categories and the wrong category is assigned to a particular case/observation - for example when a case that is exposed is incorrectly categorized as unexposed. In the case of studying tropical storms, a common method of categorizing exposures is declaring a county or parish as exposed or unexposed based on whether or not the storm track went through the county. Failure to classify exposure accurately allows misclassification bias to move the results of the study further from the true parameter (for example, classifying certain observations as exposed to a storm when they really were not, or vice-versa). Measurement error occurs when the variables being measured are continuous such as the amount of precipitation or the wind speed that was measured during a tropical cyclone.

Non-differential misclassification error. Non-differential misclassification refers to misclassification of either the exposure or the outcome, that is unrelated to the other (Aschengrau and Seage 2013). Environmental epidemiology studies are often prone to non-differential misclassification error, which will often, though not always *[in all cases—BA: this is actually not true I think—we can discuss] bias the results towards the null (Armstrong 1998).* In effect, this will weaken or obscure any associations that are present that the researcher may hope to observe in the data (Armstrong 1998). An example of a study that could be prone to this kind of bias is (Kinney et al. 2008) where Louisiana parishes were considered vulnerable to hurricane exposure based on whether or not the storm center passed through that parish. It is possible that the cases considered exposed based on living in these parishes were not in fact exposed since the storm may have passed through only a certain part of the parish. The study looked at hurricane exposure on the risk of autism, and because a diagnosis of autism likely doesn't depend on being classified as exposed to the hurricane or not, this kind of misclassification should it arise would be considered non-differential. [**Add an example from tropical cyclone impacts studies of a case where you might get non-differential misclassification error.**]

Differential misclassification error. Differential misclassification error occurs when the misclassification of the outcome is related to the misclassification of the exposure or vice versa (Aschengrau and Seage 2013). Whereas non-differential misclassification often (though not always) has the effect of moving the observed association or parameter towards the null, differential misclassification can move the observation in either direction. Differential misclassification in tropical cyclone impact studies can occur in self reported data such as in (Lieberman-Cribbin et al. 2017) where study subjects were asked to report their own flooding exposure and also mental health symptoms of depression, anxiety, and PTSD. It is reasonable to believe that self perceived exposure to hurricane related flooding would not be independent from perceived negative mental health symptoms and thus potentially contribute to differential misclassification error in this situation. ***[Define differential misclassification error.] [Add an example from tropical cyclone impacts studies of a case where you might get non-differential misclassification error.]***

Dichotomizing continuous exposure measurements. Sometimes, in research on the societal impacts of tropical cyclones, a binary exposure classification (exposed / unexposed) will be made based on applying a threshold to a continuous metric related to hazards of the storm. For example, a county might be classified as exposed or unexposed to a storm based on whether it experienced local winds during the storm above a certain threshold (e.g., gale-force winds or higher). An example where this method was deployed was in (S. C. Grabich et al. 2016). In this paper, exposure to hurricanes's effects on hazard of preterm birth was classified based on the maximum wind speed in the Florida county where the birth took place. Maximum wind speed is a continuous variable, but the study used two binary categorizations to divide it into tropical storm wind speeds, which were those greater than 39 miles per hour, and hurricane wind speeds, which were those greater than 74 miles per hour. Florida counties that experienced maximum wind speeds below 39 miles per hour were considered to be unexposed.

There are several advantages to dichotomizing continuous variables, but the general consensus in epidemiology is not to do it. The reasons it is implemented are typically because it simplifies the data and allows for easier analysis and interpretation (Naggara et al. 2011). Additionally, it is very common in clinical settings to categorize continuous variables, for example hypertensive or not hypertensive, overweight or not overweight, dead or alive, etc. (Van Walraven and Hart 2008).

For the most part however, categorizing or dichotomizing continuous variables is not ideal. One largely noted reason why is that statistical power is lost because so much information is lost when categorization occurs (Van Walraven and Hart 2008). That 100 continuous observations or data points are statistically equivalent to at leaset 157 observations has been noted in several studies (Naggara et al. 2011). This makes sense when you consider that continuous variables allow you to observe nuance in the data and perceive a dose response relationship between the predictor and response variables, should one exist. This effect is masked when categorization occurs, and even more so when a smaller number of categorical variables are used (for example dichotomization itself at 2). Generally, if you are going to categorize continuous data, it is better to use 3 or more categories rather than just two. An example of a paper that used three different bins was (Kinney et al. 2008), which explored the risk of autism after a pregnancy that included exposure to a tropical storm in the state of Louisiana. Exposure to tropical storms was classified as severe, intermediate, and low exposure, and these exposure classifications were determined based on whether or not a mother lived in a Louisiana parish that had two of the exposure factors: storm intensity and storm vulnerability. Storm vulnerability in this case was based on another dichotomy of whether or not the storm center passed through the parish of interest, and storm vulnerability was a measure of how vulnerable the inhabitants of the parish were to the effects of a storm (higher socioeconomic neighborhoods and parishes have more resources to withstand and recover from a tropical storm for example).

Another obvious problem with categorizing continuous data is that the cutoff points are often arbitrary. In the case of dichotomization, the median is often used, but there is typically no reason to assume that the median is a reasonable cutoff point, and because different samples will have different medians, this automatically makes many categorical bins difficult to compare across studies (Altman and Royston 2006). Choose optimal cutoff points that give the smallest p-values are also not great as they lead to spurious results (Altman and Royston 2006).

Not surprisingly, as with exposure misclassification, dichotomizing continuous variables can bias results. A study by Selvin showed that the odds ratios can be significantly different depending on the chosen cutoff that is implemented in a study (Van Walraven and Hart 2008). Categorical variables also can put otherwise similar observations into separate bins if they are close but on opposite sides of the cutoff (Altman and Royston 2006). While the idea of using a median as a cutoff for example is to delineate a “high” and “low” group, two individual observations that may only be a fraction different but on either sides of the mean will be classified as high and low respectively and give the false impression that they are significantly different.

It is important to note that while dichotomizing continuous variables is something that can be done for either the exposure or the outcome of interest in a study, for our purposes we are primarily interested in continuous *exposures*. This means that we are primarily interested in the effects of dichotomizing variables such as wind speed, rainfall, temperature, distance from storm center, and distance from coastline, among other factors. Many epidemiology studies will dichotomize continuous outcome variables such as blood pressure, body weight (BMI), and length of pregnancy in order to gage medical concern and priorities, but because we are concerend with creating a data framework that makes accessible storm exposure data for epidemiologists, exposure scientsits, economists, and other scientists to use, we have a priority to look at exposure variables.

Common resolutions for human impacts outcome data

We conducted a literature review to investigate the different spatial and temporal scales that were most commonly used by researchers studying tropical storm and hurricane impacts on health, ecology, and economic systems in affected areas. Spatially, the most common units tended to be the county and state level, while the temporal scale ranged from days to weeks to cumulative measures across storm events.

Spatial Scales

Data measuring human impacts often represents things that happened to individuals, and often happened at a specific geographical location. In human impacts studies, such outcomes occasionally are available at the individual level. However, often the data are not available individually, but instead as aggregations, often aggregated based on geopolitical boundaries. In this section, we describe some common spatial resolutions for outcome data from previous research on the human impacts of tropical cyclones in the United States.

Point Location

[BA: Let’s think some about the order we want for these sections. We’re making several good points / analysis here. First, we’re defining what we mean by the resolution (“point location” here). We probably want to start with that. Then we have some examples for studies that have had outcome data at this resolution. Maybe that could go next, to help illustrate the definition we’ve given. We’ve got some information on *how* the data at this scale was collected (e.g., geocoding from addresses reported from the study subjects), which I think is really interesting. Finally, we're got some text that talks about how data at this resolution could be integrated with some main formats of exposure data. We might want to end with that (or maybe even, as we work on this draft, that might go into a different section of the paper).]

Point locations are the smallest resolution of spatial data used to assess the exposure to tropical storms and hurricanes, as they represent the specific location of individual, non-aggregated observations on the outcome of interest. In many cases the point location was assessed by collecting information on the study subject's residential address through some sort of a survey (Lieberman-Cribbin et al. 2017), (Jaycox et al. 2010),(Bayleyegn et al. 2006). These surveys were often designed to assess psychological needs of hurricane survivors, as well as medical, financial, and nutritional needs. For example in (**???**) the address was provided for New York City residents in a self reported manner to look at associations between mental health outcomes and flooding data. This residential address served as a point location that could be mapped and was compared to flooding data maps created by FEMA. In other cases, point locations were recorded using a GPS device that recorded actual coordinates such as in (Hagy, Lehrter, and Murrell 2006) where specific point locations were used to take water samples were taken to measure parameters of water quality such as salinity, temperature, dissolved oxygen, and turbidity compared before and after Hurricane Ivan in Pensacola Bay, Florida. This is a pretty common practice in ecological research because point locations distributed across a landscape can be used to observe patterns taking geography into account. Point locations are also advantageous when using satellite images in conjuction with analysis of hurricane impact as illustrated in (Bianchette et al. 2009), where Landsat 5 images were used to compare vegetation damage by looking at specific trees at different elevations to assess the ecological impact of Hurricane Ivan.

The obvious advantage of a point location is that when mapped it can be overlayed with physical exposure data on a storm or storms to gage a very accurate picture of exposure, taking full advantage of high resolution in the exposure data. Since storm tracks are often spatially represented by the path of the storm's center, having point locations for the exposed units of interest means that you can more accurately measure how close each observation was to the storm's central track, and then further make conclusions based on this. Similarly, point locations can be integrated in a straightforward way with gridded exposure data, as might result from re-analysis datasets or … [check with James Done about this], as each point location can be assigned the exposure level of the closest gridded measurement.

Zip Code/County/Parish

While point locations are very useful, many of the papers cited used larger geographic areas to denote spatial exposure to storms. Zip codes (Bevilacqua et al. 2020),(Lane et al. 2013), are often used to aggregate groups of people living in a given area. Counties are higher aggregated level than zip codes (Kinney et al. 2008), (S. C. Grabich et al. 2016), (S. Grabich et al. 2016), (Schwartz et al. 2018), (Harville et al. 2010). Often these levels seem to be used when a specific metropolitan area is being looked at such as New York City with Hurricane Sandy (Lane et al. 2013), and Houstan with Hurricane Harvey (Schwartz et al. 2018). The county level is often a convenient method to use the storm path of the hurricane to quickly categorize exposed areas as in (S. Grabich et al. 2016). There are several disadvantages and pitfalls to using this spatial level. One is that not all counties and zip codes(which are called parishes in Louisiana) are the same size or have the same population, so they may not be immediately comparable. Using the county/parish or zip code also lends itself to the possibility of exposure misclassification. There are many ways that this can occur in a study on tropical storms; one common example is that counties selected as exposed are those that had the center of the storm pass through their county's physical boundaries. However it is very possible that some individuals lived in a county that was classified as exposed based on this criteria but were in a region of the county far enough away from the storm center that they were not severely impacted. That means these individuals would be classified as exposed when they really were not and it could bias the association towards the null if one existed. Alternatively, individuals who lived in a county that wasn't classified as exposed but were near the border of a county that was could be incorrectly categorized as being unexposed even if they actually experienced many of the effects of the storm.

State/Metropolitan Region

Many studies used the spatial level of entire states or specific metropolitan areas to gather information on those who were exposed. (Harville et al. 2010) is an interesting paper because it looks at the state level as well as the regional and parish level. In this paper birth outcomes in response to Hurricane Katrina are looked at in the state of Louisiana as a whole, as well as the New Orleans metropolitan area, and then finally Orleans parish which is the heart of New Orleans. Looking at these three levels is a way to compare different incident rates and other measures of associations across different spatial scales.

The state or national level is the spatial level of an ecological study and can be useful to compare the emergency preparedness and policies of different states. The potential for the ecological bias is of course present when looking at this spatial scale however, which occurs when the outcomes on the population level (typically an average), do not represent the individual outcomes very well.

Temporal Scales

Week

Week appears to be a very common unit of time used to ascertain exposure, particularly for studies that are concerned with birth outcomes and gestation during hurricane exposure (Kinney et al. 2008), (S. C. Grabich et al. 2016), (S. Grabich et al. 2016). When the week of gestation is known, the timing that the hurricane makes landfall, or has its storm center pass through a county can be matched up to this week of gestation to identify possible "critical periods" of exposure during development.

Cumulative Measures of Time

Many of the studies looked at didn't assess exposure at the moment of the storm, but rather after it had done damage.

Terms

These are terms we're using right now that we might want to iterate on, in conjunction with our colleagues on the project, to make sure we have terms that are precise and consistent across the document:

- **physical exposure data**: By this, we mean things that are measured about the storm like wind speed, rainfall, measures of flooding, and other things that might be considered more in the realm of what an atmospheric scientist or engineer might measure about the storm. We're contrasting this with data that for human impacts studies on outcomes among humans (e.g., pregnancy outcomes, economic outcomes like unemployment)
- **resolution**: We're using this right now to talk about spatial and temporal levels of aggregation. Sometimes, we're using "scales" instead, I think.

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