2nd Draft of Challenges of Integrating Physical Exposure and Human Impacts Data in Tropical Cyclone Studies

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Introduction

Tropical cyclones—which encompasses hurricanes as well as tropical storms and tropical depressions— regularly threaten coastal communities across the Eastern and Southern United States. From 2000 to 2019, tropical cyclones cost the United States at least 811 billion dollars in damages(**???** billion dollar disasters). Tropical cyclones in that same time frame resulted in 6,010 human fatalities, averaging 301 deaths per year (**???** billion dollar disasters). Tropical cyclones upset coastal communities and society by damaging property, disrupting local economies, and harming human health. This is why they are so critical to study.

Tropical cyclones are environmental disaster events that are crucial for public health authorities and scientists to understand. Human mortality is an obvious consequence of these storms, and in 1992 Hurricane Andrew left 53 residents in Florida and surrounding states dead (Ahrens 2005). However, many other chronic and long term health impacts have been observed in the aftermath of tropical cyclones. For example, researchers have observed that in utero exposure to tropical cyclones leads to adverse birth outcomes. (Kinney et al. 2008) observed higher rates of autism in children born to mothers who had higher rates of storm exposure than children born to mothers who were exposed to lower intensities. The scientific literature also reveals evidence of mental health outcomes associated with populations exposed to tropical cyclones. Survivors of tropical storms often report higher levels of depression, anxiety, and PTSD, due to reduced access to important medical and social services, property damages, poor sanitation, and displacement after storms (Lieberman-Cribbin et al. 2017).

Beyond health impacts, both mental and physical, tropical storms create incredible strains on the economies of the Southeastern United States. The average cost of a tropical cyclone event in the US is 21.2 billion per event. (**???** billion dollar disasters). Large population displacements often result from tropical cyclone events as well, such as the migration of Puerto Ricans to Florida after Hurricane Maria. (Scaramutti et al. 2019)

Clearly, tropical cyclones dramatically impact the social, economic, and physical wellbeing of coastal communities. These extreme weather events represent an environmental health threat that is not going to disappear, and given that coastal regions of the Southeastern US are experiencing population growth, it is likely that higher numbers of people will be put at risk in the future. Avoiding these risks is not possible, but building resilience in communities after they experience tropical cyclone events is key to mitigating damages and preparing for future disasters. Creating lasting and resilient communities in areas prone to tropical cyclones requires that researchers understand which populations and locations are at the greatest risk for negative exposures to tropical storms. High quality data allows researchers to assess where in space and time tropical storms occur, and also where in space and time individuals and populations are experiencing impacts from these storms.

The key challenge for multidisciplinary teams to assess the human effects of tropical cyclones is integrating data from across disciplines. For example: 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 may also result from data collection efforts during or after the storm by atmospheric scientists and engineers seeking to characterize a storm. Researchers studying the human impacts of these storms, including epidemiologists, economists, and social scientists are interested in this data as well, but the differences in temporal and spatial resolution makes the data harder to use. Resolving physical exposure and human impact datasets is challenging because the human impact data and physical exposure data often do not have congruent resolutions.

Here we explore cases and implications of integrating data at different temporal and spatial scales, focusing as an example on human impact studies of tropical cyclones in the US. We begin by investigating the meteorological methods used for measuring physical exposures, and contrasting these with the ways in which human impacts data is used . We then describe the main spatial and temporal scales used, and finally assess some of the consequences that result from integrating physical exposure data with human impacts data.

Measuring Physical Exposures

Atmospheric and weather data are designed to give a picture of meteorological activity over vast geographic spreads as large as entire continents or oceanic basins. To acheive this, data is often recorded by sensors and instruments at fixed weather monitoring stations, in vast monitoring systems that are designed to automatically record a data point at a fixed interval of time. These monitoring systems are often the result of long-standing weather projects such as the National Hurricane Center Data Archive from NOAA (National Oceanic and Atmospheric Administration), and the NWS (National Weather Service). This data is often narrow in temporal and spatial resolution, and large in geographic scope.

Wind Speed and Direction

Wind speed is an extremely important element of tropical cyclones. To even be classified as a tropical cyclone, a storm must have wind speeds in excess of 74 miles per hour (64 knots).

Meteorologists and atmospheric scientists use ground based wind instruments in set locations to measure wind speed and direction. One such instrument is called a wind vane. These can take on a variety of appearances such as wind socks at the airport, but they are essentially arrows that always point in the direction the wind is blowing. Anemometers measure wind speed by recording the rate of rotation of moving cups on a free moving shaft. An aerovane can measure both wind speed and wind direction and can be attached to a recorder to give continuous measurements. In order to be accurate and effective, these ground based wind instruments must be placed above the roofs of buildings so that they can be exposed to free flowing air. Since this is not always the case, wind observations can consequently be erratic in nature.

Above ground, geostationary satellites, which are positioned above a particular location can measure wind speed and wind direction by observing the direction that clouds move in a given amount of time. Doppler radar can also be used to measure wind speed and direction.

Precipitation

It is important to measure precipitation from tropical cyclones because not only does this give an indication of the cyclone's magnitude, but it also corresponds to damaging effects such as flooding.

Rain gauges are the most well known instrument for measuring precipitation, but there are several different types of gauges. A standard rain gauge is simply a funnel shaped rain collector that is attached to a tube with measurements on the side. Measurements of rain less than 0.01 of an inch in a rain gauge are referred to as trace amounts. Tipping bucket rain gauges send electrical signals to a remote sensor every time a system of two buckets moves due to a known amount of water filling one of the buckets. Because a small amount of rain is lost whenever the buckets tip, this way of measuring rain is always an undercount. However, this is the type of rain gauge used by the automated weather stations.

Finally, similarly to wind speeds, radar and doppler radar can also be used to gauge precipitation. These technologies allow scientists to actually see the inside of a cloud and understand the amount of precipitation in that cloud.

Excessive precipitation, sometimes in concert with storm surges, often leads to flooding; this is a more severe physical exposure that researchers are interested in. Stream gauges are often used to measure flooding, and tide stations, high water marks, and temporary barometric pressure sensors are used to measure the magnitude of storm surges.

Measuring Human Impacts

Where physical exposure data is often expansive and specific, owing to well established networks of weather monitoring stations, data on human impacts are spatially and temporally located within geopolitical, cultural, and administrative boundaries. This type of data is available often in the form of census records, hospitalization records and vitals statistics from hospitals and public health departments, disaster insurance claims, schools, and other systems that record human activities. Unlike the physical exposure data, these sources are often aggregated by geographic region and time, often out of convenience, or a need to preserve the anonymity and privacy of the people whose data is being used. Researchers also will use such secondary datasets and sources to compare with primary data sources. For example in (Lieberman-Cribbin et al. 2017), self reported flooding exposure data was compared to FEMA flooding exposure data. This goes to show that different disciplines have different aims and needs, and this creates spatial and temporal misalignment when multidisciplinary research is conducted.

[EXPLAIN SEVERAL DIFFERENT METHODS FOR HUMAN EXPOSURES: SURVEYS, CENSUS DATA, INSURANCE CLAIMS, ETC.]

Spatial and Temporal Misalignment

Differences in spatial and temporal scales are related to the study question that researchers are asking. If a study is concerned with birth outcomes for example, having weather data on the windspeed every several seconds may not be relevant, because birth outcomes related to storm exposure in utero may operate on a longer time scale. In (S. C. Grabich et al. 2016), the researchers looked at gestational periods and defined pregnancies as exposed to tropical cyclones if they happened before 20 weeks of gestation. If the researchers had been interested in a different question, for example acute injuries due to direct storm exposure, or hospitalizations, they would have chosen a smaller time scale. There is no correct spatial or temporal scale that works well for all research, it all depends on what is being asked and how that can be ascertained. Different scales allow the researchers to make certain inferences and determine how the results of a study can be interpreted.

If spatial and temporal misalignment are a result of different disciplines using different methods, asking different questions, and collecting data from different sources, then it is important to understand what those temporal and spatial scales are. The remainder of this section will highlight the most common spatial and temporal scales typically used in tropical cyclone studies. These scales were chosen after conducting a literature review that covered a wide range of human impacts from tropical cyclones. First we will describe spatial scales starting from the smallest resolution of point locations, working up to the level of metropolitan areas and states. Next we will describe temporal scales most commonly used in tropical cyclone studies and again work from smallest to largest resolution.

Spatial Scales

The spatial scale that a researcher uses varies depending on the data available or sampling method used. In human impacts data finer spatial scales will correspond more often to individuals or households, while larger spatial scales will correspond to regions, states, or even countries. Physical exposure data is often at a small point location or a grid, based on where weather monitoring sensors are placed. In the following section we will outline the most common spatial scales used in tropical cyclone studies and include some examples from the literature where they were employed.

Point Location

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, researchers collect information on the study subject's residential address through some sort of a survey to assess point location (Lieberman-Cribbin et al. 2017), (Jaycox et al. 2010),(Bayleyegn et al. 2006). These surveys are often designed to assess psychological needs of hurricane survivors, as well as medical, financial, and nutritional needs. For example in (Lieberman-Cribbin et al. 2017), New York City residents provided their address 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, a GPS device is used to record coordinates that mark a specific point location. An example is (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 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.

Weather sensors and monitors are typically stationary and planted at fixed locations, either as part of monitor networks at various stations, or as temporarily planted fixtures for measuring the effects of particular storms. As such, their point locations are typically well defined.

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 gauge 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 allows researchers to more accurately measure how close each observation was to the storm's central track, and make further conclusions 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.

[Once we give examples, we should talk about what level the physical exposure data was recorded as. Did it line up exactly? Grided data. Some studies avoid the problem by creating a proxy (ex: dist from the storm track).]

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 at a higher aggregation 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 after Hurricane Sandy (Lane et al. 2013), and Houstan after Hurricane Harvey (Schwartz et al. 2018).

Aggregating exposure at the county level is convenient because it utilizes some of the most established methods for assigning exposure status: the storm track trajectory, and FEMA presidential disaster declarations (S. Grabich et al. 2016). The storm track trajectory is typically the path that the tropical cyclone takes, and although the counties immediately crossed can be categorized as exposed, there are methods to calculate distance from the storm center that allow for estimation of exposure at various distances by establishing exposure thresholds.

There are several disadvantages and pitfalls to using this spatial level. For one, 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 makes it easier for researchers to misclassify exposure. 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 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. These individuals would be classified as exposed when they really were not and it could bias an apparetn association towards the null. Alternatively, individuals who lived in a unexposed county, but were near the border of an exposed county 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 researchers observed birth outcomes in response to Hurricane Katrina in the state of Louisiana as a whole, the New Orleans metropolitan area, and 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

Thanks to scientitific institutions such as NOAA and the National Weather Service, there are wide networks of sensors and monitoring equipment established across the United States that are capable of recording physical exposure data at a fine enough level as to render it almost continuous. It is possible to know the wind speed, amount of rainfall, and air temperature at very fine temporal scales throughout the duration of a tropical cyclone event. Human impacts data however, is typically not available at such a fine scale, nor is such a scale sometimes even relevant. Whereas physical exposure data may be collected in real time during the storm, many of the human impacts that researchers are interested in may be only known after the storm, and thus estimations may have to be made of what happened in the past. Below are some examples of time scales that are more applicable to a human scale, and why aggregating physical exposure data to these units of time may be necessary.

Seconds/Minutes/Hours

The finest temporal spatial scales are not very commonly used when studying human impacts, as there are very few scenarios where the effects of tropical cyclones on populations and individuals can be studied so precisely. Mental health outcomes, pregnancies and birth outcomes, economic effects, and destruction are usually assessed after a storm has passed.

However, these fine temporal scales are usually the temporal scales physical exposures are measured at. Wind veins, barometers, and record this information

Day

In the event of a tropical cyclone, there are several situations in which the temporal unit of a day may be used to analyze exposure. Physical exposure data from tropical cyclones will typically be available at this scale anyways, but some studies will look at time series and use daily exposure data from hospitalizations and visits to the emergency room.

One study, [zahrah2013daily] looked at casualty counts per day for counties in the Southeaster United States that were exposed to tropical cyclones.

Week

Week is 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.

In the North Atlantic Basin, tropical cyclones typically occur between June and November, and so sometimes month to several month periods are used to aggregate the temporal exposure to them.

Cumulative Measures of Time

It is often the case that specific physical exposures are not considered in real time to ascertain human impacts. Instead, human impacts are assessed after the storm has passed, often noting the number of days or weeks that have passed since the hurricane made landfall. This method is common when assessing damages, recovery efforts, and when human impacts are self reported. When this is the case, it is often useful to take an aggregate exposure an aggregate measure of physical exposure corresponding to this time frame, such as the maximum wind speed or maximum flooding level over the period of time being studied.

Implications of not improving this integration

Temporal and spatial misalignment poses certain challenges to researchers investigating the human impacts of tropical cyclones. There are several methods for integrating exposure data and outcome data that are at different scales, namely aggregating, interpolating, and matching data. These integration methods allow researchers to create estimate associations of human impacts with particular storm exposures, and this is key for understanding the ways in which vulnerable populations are susceptible to tropical cyclone exposures.

When researchers are confronted with exposure and outcome data at different temporal and/or spatial scales there are a few things they can do. One is to aggregate whichever dataset is at a finer resolution to match the dataset that is already at a broader resolution. Often when this method is employed, a specific exposure variable may be available for analysis at a very fine resolution. For example, many weather monitoring sites across a county may be recording wind speed, but researchers will take a single value to represent wind speed in the entire county, possibly by taking average or a maximum value. This is a what is happening when a metric such as maximum wind speed is being used as a proxy for tropical cyclone intensity or exposure as in [grabich2016measuring].

Misalignment doesn't only occur when data points are at different scales however. Sometimes there are situations in which researchers will have exposure and outcome data at the same spatial scale, often a point location. The problem is that the point locations are not the same. A researcher may have access to exposure data from a weather monitor at a point location that gives the amount of rainfall received during the same storm, and then several households nearby that are also point locations, but varying distances from the weather monitor. In a situation such as this, the researcher will have to interpolate data, or else find some other way of matching the point location with the dataset.

The aformentioned methods above for integrating datasets from physical exposures and human impacts come with the important caveat that they introduce bias and error into studies. Bias and error impact the internal validity of a study by obscuring the true association between an exposure and certain outcome relating to human impacts. Bias and error can have the affect of moving an estimate of an association away from the true paramater, as well as reducing precision of that estimate.

In this last section we will explain the implications of integrating datasets from different temporal and spatial scales. There are many sources of error and bias that can be introduced and we will explain how ecological bias, exposure misclassification and measurement error arise from datasets that are aggregated and interpolated. We will also explain what effect these forms of error and bias have on the estimate of the associations we are interested in.

When Data Have Different Scales

When researchers have physical exposure data at a very fine resolution, perhaps even continuous, and human impacts data at a more aggregate level, it is common and practical to aggregate the physical exposure data. This same practice could also work the other way around, aggregating human impacts data to a physical exposure dataset with a narrower spatial and temporal resolution. In any case, when dealing with aggregated data of any kind, it is important to realize that information on the individual level is lost. Researchers should be mindful when aggregating data, particularly continuous data, that they are losing information. In this section we will discuss some of the major implications of aggregating data which include ecological bias, misclassification and measurement error, and the process of categorizing continuous data .

Ecological Bias

Physical exposures to tropical cyclones, as well as human impacts, are observed across spatial gradiants, and though specific point locations may exist for a weather monitor recording maximum wind speed or rainfall, that point location data is often aggregated to a larger spatial unit. For example, several weather monitors at specific point locations recording maximum wind speed may be replaced by the highest wind speed in a specific county. Data such as this is known as ecological data, aggregate data, or contextual-level data. Studies that use such data are known as ecological studies (Sedgwick 2014). Ecological bias occurs whenever the aggregate association between an exposure and an outcome does not properly reflect the association on the individual level (Greenland and Morgenstern 1989). There are times when this is not a concern, such as when the aggregate is a count. For example in (Zahran, Tavani, and Weiler 2013), the daily casualty count was reported for individual counties in the Southern United States, using count data from the Spatial Hazard Events and Losses Database. However, when estimates derived from ecological studies are used to infer individual estimates, ecological bias will likely be present. Especially when there is heterogeneity present in an aggregated population, an ecological estimate should not be taken to be representative of individual estimates.

Categorizing Continuous Data

In addition to using larger spatial designations, researchers aggregate the physical exposures themselves, simplifying continuous measurements down to a single exposure metric. While aggregate values often represent the mean of all the values recorded, weather data is typically assessed by the maximum value. Regardless, aggregating physical exposure data requires researchers to categorize continuous data, which involves choosing appropriate thresholds.

Thresholds are often used to assign exposure status to individuals or populations (often using a county as proxy for a population). For example, a county may be classified as exposed or unexposed based on local winds exceeding a threshold (e.g. gale-force winds or higher). S.C. Grabich et al. 2016 classified hurricane exposure in a Florida county using maximum wind speed. Maximum wind speed is a continuous variable, but the study used binary categorizations to divide it into tropical wind speeds, classified as greater than 39 miles per hour, and hurricane wind speeds, classified as greater than 74 miles per hour. Florida counties experiencing maximum wind speeds below 39 miles per hour were considered unexposed. In this example it is noteworthy to examine that all the Florida counties in this paper likely experienced hurricane winds somewhere on this spectrum, but categorizing that continuous data made exposure much simpler and concrete.

The Saffir-Simpson scale is an example of how entire storms are often classified by their maximum wind speed. Forecasters classify hurricanes into categories on the Saffir-Simpson scale based on maximum sustained surface wind speed. This is defined as the peak one minute wind speed at a height of 10 feet over an unobstructed exposure (Taylor et al. 2010). The Saffir-Simpson scale uses five different bins to classify varying levels of wind speed and determine the severity of a storm. The first level, Category 1 is designated for hurricanes and tropical storms with maximum wind speeds of between 64 - 82 knots and is generally considered dangerous to people, livestock, and pets from the hazard of flying and falling debris (Taylor et al. 2010). On the higher end of the scale, Category 5 designates hurricanes with maximum wind speeds above 137 knots and is considered to have catastrophic effect on damage and a high probability of injury or death to people, livestock, and pets even if they are sheltering indoors (Taylor et al. 2010). An important limitation of the Saffir-Simpson scale is that it doesn't account for other hurricane-related impact variables such as storm surges, flooding, and tornadoes (Taylor et al. 2010).

Another scale used to categorize wind speed is the Beaufort scale, created by Admiral Sir Francis Beaufort, used to classify wind speeds both over land and sea. While the Saffir-Simpson scale is only designated for wind speeds that are already at hurricane levels (greater than 64 knots), the Beaufort scale considers the wind speeds below this. The scale ranges from Force 0 (0-1 knots and calm) to Force 12 (64 to 71 knots and hurricane). Other interesting parts of the scale include Force 3 (4-6 knots) which is a gentle breeze, and Force 8 (34-40 knots) which is considered a gale.

Despite several advantages to dichotomizing continuous variables that we just discussed, the general consensus in epidemiology is not to do it. Statistical power is lost because so much information is lost when categorization occurs (Van Walraven and Hart 2008). 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 researchers categorize data, 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, because this will capture more of what the data that would otherwise be lost. 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. The study authors classified tropical storm exposure as severe, intermediate, and low exposure, and these exposure classifications were determined based on whether a mother lived in a Louisiana parish that had both of the exposure factors of interest: storm intensity and storm vulnerability. Storm vulnerability in this case was based on another dichotomy: whether or not the storm center passed through the parish of interest. 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. Because different samples will have different medians, this automatically makes many categorical bins difficult to compare across studies (Altman and Royston 2006). Further, choosing optimal cutoff points that give the smallest p-values can lead to spurious results (Altman and Royston 2006).

Not surprisingly, 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 can also put otherwise similar observations into separate bins if they are close but on opposite sides of the cutoff (Altman and Royston 2006). Choosing a median as a cutoff is intended to delineate bins, but if the bins are 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.

Although using a single exposure value can simplify analysis and interpretation, particularly over an extended temporal scale, there are some obvious drawbacks to relying on one single aggregate value. For example, the Saffir Simpson categories typically correspond only to the geographic point location where the maximum wind speed was observed (Taylor et al. 2010). Hurricane Wilma in 2005 for example, was a Category 3 hurricane when it made landfall on the southwest coast of Florida, but it created Category 1 and Category 2 conditions for the more populous Miami-Dade, Broward, and Palm Beach counties when it finally reached them (Taylor et al. 2010).

Misclassification and Measurement Error in Aggregating Data

When aggregating data, another concern that arises is misclassification or measurerement error. 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. Failure to classify exposure accurately(for example, classifying certain observations as exposed to a storm when they really were not, or vice-versa), allows misclassification bias to move the results of the study further from the true parameter . 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.

Environmental epidemiology studies are often prone to misclassification error because the methods of assessing exposure are not always congruent with the way that researchers conduct human impact studies. It is easy to map the path of a tropical cyclone's center, and categorize every county it passes through as an exposed county. However, this information by itself would not give the researcher any information about population centers that the storm passed through or near to. A town within an exposed county may or may not have been close to the storm's path. Conversely,a town in an unexposed county could be located very close to the border of an exposed county, and even be closer to the storm's track than a different town within that exposed county. 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. Never the less, all cases in a parish are considered exposed or unexposed in the aggregate.

A potential solution to this problem of misclassification of populations is through the use of dasymmetric mapping. This is a method that creates heat maps, using different colors to illustrate differences in population density among other things. Overlaying storm tracks on dasymmetric maps is a method that could be employed to record differences in

When Data Have the Same Scale but are at Different Locations

Sometimes, researchers may have access to data that is down to the point source, both for physical exposures and also for human impacts. Very likely however, these point sources will not be the same. Here the issue is not of integrating different resolution levels, but rather of matching different point locations. Weather monitoring stations may be set up regularly in a geographic region, but the human impacts point locations could be tied to a residential address.

One way to resolve this spatial misalignment is to assign exposure to the residential addresses based on the closest weather monitoring station (Kim, Sheppard, and Kim 2009). This is a common method that is employed in many other areas of environmental epidemiology, including studies on the impacts of wildfire smoke plumes and urban smog on respiratory health. Typically, a distance threshold will be determined for a monitoring station or a sensor, and any residence within that distance will be assigned an exposure value from that monitoring point.

There are several drawbacks to assigning exposure to human residences based on distance from a weather monitoring stations. One of them is that in more rural areas, in situ observations may be sparse and this limits the information between monitors, and diminishes the accuracy of exposures assigned to individuals located between those monitors (Gan et al. 2017).The exposed population is also reduced when you rely on distance from monitoring sites, because you can only include individuals who are close enough to reasonably be assigned the exposure from that site (Lassman et al. 2017). This can be a problem, as large populations are often required for detection of health impacts. Depending on the exposure of interest, topography, climate, and localized weather patterns will also render sites beyond a limited threshold distance from the site as unrealistic to be assigned the value from the monitoring station.

Other limitations: storm events could blow away monitors (damage sensors) or the rain can come down in slants that make measurements less accurate. Issues with a radar asystem are different from issues with a ground based monitoring system.

Another method of assigning exposure to spatially misaligned individuals is to interpolate. Spatial interpolation is the prediction of values or metrics of specific points within a defined region based on some sort of spatial model (Li and Heap 2014).

Kriging is one such method that creates continuous spatial surfaces for understanding environmental variables like air pollution, minerals, soil, and meteorological conditions (Liang and Kumar 2013). It is a type of Generalized Least Square Regression Algorithm (Li and Heap 2014). This method has been used extensively in modeling the effects of air pollution in places like California, as was done in (Kim, Sheppard, and Kim

2009) to look at air pollution exposure in Los Angeles, California. The study utilized a kriging model and as well as using the nearest weather monitoring station to assign air pollution exposure to residential locations in Los Angeles. Kriging is widely applicable to studies of tropical cyclones as well. Researchers in South Carolina used kriging interpolation to analyse rainfall data and create spatio-temporal model in 2015 during a particularly strong storm season.

Creating a surface, something using a model. This brings in other stuff. Kriging is only based on PM2.5 (if studying wildfire smoke). Modeling would bring in other things like weather.

3rd category: modeling.

Mention somewhere that homogenous exposures over large areas mean that it doesn't matter what method you use, maybe use the most simple, because otherwise this will be more computation time and it is harder to interpret.

Misclassification for Same Scale Different Locations

The obvious goal of assigning tropical cyclone exposures to individual point locations by matching values from the nearest monitoring site or spatially interpolating, is to estimate exposure values accuarately. This is crucial to avoid exposure misclassification. The more spatially heterogeneous that an environmental exposure is, the more room there is for exposure misclassification to occur. In studies of wildfires and air pollution, concentrations of PM2.5 and other air pollutants can very greatly within relatively small spatial areas. Other factors like windspeed and rainfall however, are fairly homogenous across spatial areas. This means that interpolating and assigning exposure based on the nearest monitoring sites may result in less exposure misclassificationhave. Tornadoes on the other hand tend to be very localized and can easily be overlooked with these methods.

When assigning exposure to an individual point location based on the nearest monitoring site, the further this location is from the monitoring site, the more likely it is that the monitoring site won't reflect an exposure estimate accurately. Topography, complicated weather patterns, and other things could complicate this measurement.

When interpolating, the environmental exposure of concern will partially determine the potential for misclassification. Using the examples from above of windspeed and rainfall, it is unlikely that much misclassification would occur over a spatial interface since they are homogenous over large areas.

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