

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. 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 later 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) found higher levels of PTSD in New York City residents who were exposed to flooding after Hurricane Sandy. 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, CPI-adjusted (??? billion dollar disasters).

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. This requires data that 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.

Multidisciplinary teams of researchers are exploring this using different datasets, however a key challenge 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 reasons that spatial and temporal misalignment exist in the study of tropical cyclones. 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.

Physical Exposures

Atmospheric and weather data have long been designed to give a picture of meteorological activity over vast geographic spreads as large as entire continents or oceanic basins. To achieve this, data is often recorded by sensors 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.

Storm Tracks

Tropical cyclone storm tracks refer to the paths the storms take, and can be displayed on maps to visualize where the center of the storm (the eye of the tropical cyclone) passes through. In the North Atlantic Basin, tropical cyclone paths have a tendency to move westward first, then curve north and sometimes northeastward before ending, although some storm tracks take very messy and circuitous paths. Satellite imagery and remote sensing can be used to detect the paths of tropical cyclones and hurricanes, and ground monitors measuring wind speed can also detect the movement of the storm. The location of the center of a tropical cyclone can be documented at specific point locations at different times, meaning that it has a very narrow spatial and also temporal resolution.

One source of data on tropical cyclone storm tracks is the Hurricane Data second generation dataset (HURDAT2) which has information on the point location of storm centers, wind speed, and atmospheric pressure in six hour intervals of North Atlantic tropical cyclones since 1851 (Deryugina 2017).

Oftentimes storm tracks are used in tropical cyclone studies to assign exposures. Sometimes, distance from a storm track is used to assign counties or zip codes as exposed, as in (???). If distance from storm track is used to assign exposure, a threshold will have to be chosen to determine whether or not a county or zip code is exposed. Larger distance thresholds will increase the number of counties defined as exposed, and potentially overestimate exposure. Smaller distance thresholds will decrease the number of counties defined as exposed and potentially underestimate exposure. In either case, misclassification of exposure could arise.

Other times, exposure to a tropical cyclone is assigned only if the storm track passed through a county or zip code. This is the approach that was used in (Kinney et al. 2008). Populations are not typically distributed in a uniform pattern across these spatial areas, and so using this method to assign exposure could also result in exposure misclassification for communities that are close to the storm track but not in the county or zip code that the storm track passed through. The reverse of this, where communities in exposed counties or zip codes are actually located farther away from the storm track is also plausible.

Wind Speed and Direction

Wind speed is a common way to characterize exposure to 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, such as wind vanes, anemometers, and aerovanes. 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.

Wind speed is often used as a measure for assigning exposure, often by choosing a threshold wind speed that if attained in a zip code or county, makes it exposed. (Yan et al. 2020) used the sustained maximum wind speed recorded at the center of counties. In this example counties were considered exposed to tropical cyclones if the sustained maximum wind speed was greater than 21 meters per second. Because this wind speed is taken from a monitor at the center of the county, it may not be representative of wind speeds in other parts of the exposed county, again contributing to potential misclassification of exposure.

Another study that used wind speed to assign exposure was (Parks et al. 2021), which categorized counties as exposed to tropical cyclones on days that they experienced peak sustained wind greater than or equal to 34 knots when the the cyclone was at the point of closest approach to the county.

Flooding and Storm Surges

Due to intensive precipitation, and the threat of storm surges during and after tropical cyclones make landfall, flooding is a major consequence that has a number of impacts on the infrastructure, safety, and economic strength of communities. Flooding accounts for about 75% of declared federal disasters, costs an average of \$8 billion in the US annually, and results in over 90 fatalities on average each year. [USGS, 2016]

There are several methods for measuring flooding and creating geospatial maps to show the extent and impact of flooding. One method is to measure high water marks. Typically, this involves sending people out to specific locations to record the high water marks, but this method is costly, requires intensive labor, and is difficult to achieve during or after flooding disasters (Li et al. 2018).

Another method is to use data from stream gauges. The United States Geological Survey (USGS) maintains stream gauges at monitored locations along bodies of water that regularly record information on water height and stream flow, often updating every fifteen minutes (Li et al. 2018). There are some limitations to this method as well, for example these stream gauges are not systematically installed along water ways, meaning that information is not uniform, and the stream gauges are not useful if the water level rises above the limit of ground based gauges or washes gauges away entirely (Li et al. 2018).

Satellite imagery, aerial photography, and remote sensing can also be used to assess the extent and damage of flooding in the aftermath of tropical cyclone disasters, but issues pertaining to cloud cover and inclement weather can make high quality, consistent, and clear images difficult to achieve and therefore use in analyzing impacts (Li et al. 2018).

Human Impacts of Tropical Cyclones

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.

Health Impacts

Tropical cyclones studies have documented associations between exposure to tropical cyclones and a number of health outcomes such as increased hospitalizations due to cardiovascular and respiratory effects (Yan et al. 2020), autism in children from in utero exposure (Kinney et al. 2008), risk of preterm birth (S. C. Grabich

et al. 2016), adverse mental health outcomes such as anxiety, depression, and PTSD (Lieberman-Cribbin et al. 2017),(Scaramutti et al. 2019),(Bevilacqua et al. 2020), increased risk of hypertension (Ferdinand 2005), and injury and death (Lane et al. 2013). The health data that informed these studies comes from a number of public health agencies, both governmental and non-governmental that collect extensive information pertaining to deaths, acute and chronic illnesses, injuries, birth and pregnancy outcomes, and mental health conditions. This data provides researchers with a wealth of information on health related human impacts of tropical cyclones.

Certain general health information can be accessed from data published by the National Vital Statistics System of the National Center for Health Statistics (NCHS) (Aschengrau and Seage 2013). This organization has registration offices in every U.S. state, Washington D.C., and New York City. Vital statistics from birth certificates for example, are recorded and verified by medical professionals and submitted to local health departments, which submit this information to state health departments, which eventually send it to the NCHS (Aschengrau and Seage 2013). Because local health departments typically exist at the county and state level, this health information will also be aggregated at those levels.

Mortality data is also collected in the US by the NCHS through a program it administers called the National Death Index (Aschengrau and Seage 2013); this particular data has to be obtained through offices at the state level. Death certificates themselves will give the information of the events that led to death, something of interest when determining impacts of tropical cyclones. There are many other sources of health data that contain information pertinent to impacts from tropical cyclones such as the National Health Interview Survey, National Notifiable Diseases Surveillance System, Planned Parenthood Federation of America, Center for Disease Control, Pregnancy Risk Assessment Monitoring System, and many others (Aschengrau and Seage 2013). The key is to understand that these data come from hospitals, public health departments and other agencies at county and state levels.

Social and Economic Impacts

There is a wide variety of social and economic costs associated with tropical cyclones. Often large populations of people are displaced after tropical cyclone events, such as the Puerto Ricans who migrated to Florida after Hurricane Maria (Scaramutti et al. 2019). Another crucial consequence of tropical cyclones is that homes, businesses, and community infrastructure are damaged, often severely. This destruction alters local economies, sometimes leading to unexpected economic consequences.

To study social changes after tropical cyclones, demographic details such as race, ethnicity, socioeconomic status, age, and political affiliation are interesting and often insightful details of information that can help to shine a light on the human impacts of tropical cyclones. For many researchers, this data can be gleaned from the US Census. The US Census is a valuable source of information that is updated and compiled every ten years by the US Bureau of the Census on many variables including ancestry, racial background, mortgage, occupation, household size, etc.(Aschengrau and Seage 2013).

To quantify economic impacts of tropical cyclones, there are a variety of metrics that are used by researchers, such as studying how employment and earnings change before and after a tropical cyclone event. (Belasen and Polachek 2008) built a generalized difference-in-difference (GDD) model to study the effects of hurricanes on county-level employment and county-level average quarterly earnings per worker in the state of Florida. Though the state of Florida was studied here, results from looking at the county level showed differences in economic impacts depending on the severity of the hurricane, and the intensity of it when the county was hit by it.

Individual tax returns are another resource that researchers can use to estimate economic impacts from tropical cyclones. Tax returns and tax records can provide a wealth of information on the financial and economic situations of large numbers of individuals before and after a tropical cyclone event because they can be linked to individual residential addresses (a point location), which allows researchers to identify residents of an area before a tropical cyclone, and they can give information about wages, salaries, self-employment, unemployment insurance, the Social Security Disability Insurance program, and retirement accounts (Deryugina, Kawano, and Levitt 2018). (Deryugina, Kawano, and Levitt 2018) did just this to study the economic impact of Hurricane Katrina on the city of New Orleans, by collected information on

individual federal tax returns and third party information returns filed between 1999 and 2013. Because tax returns are linked to individuals with known residential addresses, tax returns allow researchers to observe economic impacts at a point location.

Another great resource researchers can utilize for studying economic impacts of tropical cyclones is from insurance claims.

Spatial and Temporal Scales and Misalignment

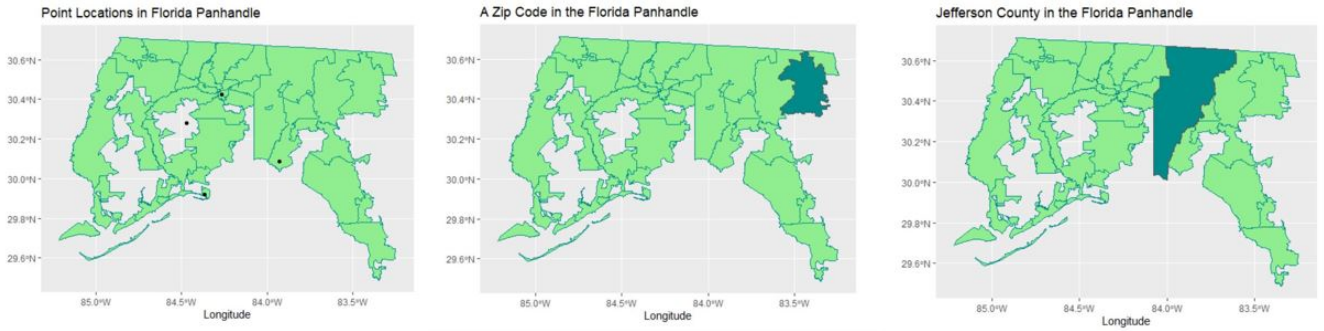
Questions about the human impacts of tropical cyclones are multidisciplinary, and as such require datasets from different and sometimes seemingly disparate sources. The physical exposures of tropical cyclones that were mentioned above such as wind speed, storm tracks, precipitation, and flooding data come from monitors that are at fixed locations, sometimes at airports, sometimes the center of a county, and other times in organized gridded systems. In contrast, the data on human health, social, and economic impacts will come from hospitals, schools, census reports, insurance claims, tax returns, and other documents and records coming from typically more aggregated spatial levels like counties.

Differences in spatial and temporal scales are also 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, 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.

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 residential or business addresses, while larger spatial scales will correspond to zip codes, counties, states, or even countries. Physical exposure data is often at a small point location, sometimes within a larger 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, that can be characterized by a specific latitude and longitude. Meteorological instruments, monitors, and sensors that collect information on physical exposures are at this spatial level, but human impacts data can also be represented at this spatial level.

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.

The obvious advantage of knowing the point location of a human impact 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 data resolution. Since storm tracks are often spatially represented by the path of the storm's center, having point locations like geocoded residential addresses, allows researchers to measure how close individuals are to the storm's central track, and therefore categorize their exposure. 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 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 Houston 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). Information on human impacts such as birth outcomes, hospitalizations, tax records, and demographic data are often recorded at this spatial level as well.

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 apparent 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. It can also reveal inequities in government response to natural disasters. For example, in (Willison et al. 2019), researchers quantified the federal responses to Hurricanes Irma, Harvey, and Maria in Texas, Florida, and Puerto Rico. They determined that in terms of federal spending and staffing, Hurricane Maria in Puerto Rico was not responded to in a manner commensurate with damage and need for aid compared to Hurricanes Irma and Harvey in Texas and Puerto Rico.

Temporal Scales

Thanks to scientific institutions such as NOAA and the National Weather Service, there are large networks of sensors and monitoring equipment established across the United States that are capable of recording physical exposure data at a fine temporal level. 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.

Real Time (Minutes, Hours)

Many physical exposures, like the ones mentioned above (storm tracks, wind speed, flooding, precipitation, storm surges) are recorded by various instruments and measuring devices both on the ground and above using radar, satellite imagery, etc.

Day and Week

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, (???) looked at casualty counts per day for counties in the Southeastern United States that were exposed to tropical cyclones.

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.

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.

Other times, it is useful to look at cumulative measures of time but also divide that period up by a certain time unit. For example, in (Grech and Scherb 2015), male and female birth ratios were observed monthly from January 2003 to December 2012 in order to observe trends before and after Hurricane Katrina. In this example we can see that a large time frame of several years is studied, but it is divided by months.

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 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 an 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 (S. Grabich et al. 2016). In (Shao et al. 2017), the maximum wind speed when a tropical cyclone made landfall in a particular coastal county was used to assign that particular county's exposure.

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 point location resolution. The problem is that the point locations are not the same, or do not line up with each other. 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 aforementioned 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.

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 gradients, 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 maximum wind speed at the center of the 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). Using the maximum wind speed at the center of a county is often the measurement used to determine exposure status. (S. 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). (Shao et al. 2017) used this scale to assign wind speed categories to counties along the Gulf Coast in a study assessing perceptions of risk to tropical cyclones. (Belasen and Polachek

2008) used this scale as well in a study that compared hurricane intensities to average earnings in different counties. Hurricanes with categories one, two or three were considered lower intensity, and hurricanes of counties four and five were considered high intensity.

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.

There are times when thresholds of human impacts are also used to assign exposure. In (Christopher 2017), pregnancy outcomes were studied in relation to exposure to tropical cyclones and tornadoes. Birth outcomes to, others who had been pregnant during the cyclone disasters in counties exposed to the storm were compared to birth outcomes of mothers in unexposed counties. In this study, exposure was analyzed by using thresholds of fatalities (greater than ten deaths), and property damage (greater than \$10 billion).

Despite several advantages to dichotomizing continuous variables that we just discussed, there are several limitations to consider. 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 variation in 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 measurement 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 dasymetric 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 dasymetric 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 system 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 accurately. 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 vary 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 misclassification. 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.

Conclusion/Discussion

The aim of this paper has been to show that studying the human impacts of tropical cyclones requires use of multiple datasets from different sources, at different temporal and spatial scales, and resulting from different data collection methods. We've shown how physical exposure data from tropical cyclones usually comes from point location monitors and sensors such as rain and stream gauges, wind vanes, at weather stations that are often a part of large scale networks operated by NOAA and the NWS. We've shown how in contrast to this, that data on human impacts comes from administrative sources at hospitals, schools, and governments, often at the level of the zip code or county. Because this isn't a natural

Reverse Funnel

(Small) - We've discussed the data sources, temporal and spatial scales, and methods of collecting data on human impacts and physical exposures related to tropical cyclones.

- We’ve talked about how different temporal and spatial scales make it challenging to immediately use this data.
- We’ve discussed the main methods for integrating data at different spatial/temporal scales: aggregating, interpolating, matching.
- We’ve discussed the implications these integration methods have, and what effect they may have on the observed associations with regard to error and bias.

(Mid-Funnel) - Error and bias are bad because they make the results of tropical cyclone studies less generalizable.

- Less generalizable studies make it harder to predict human impacts in the future and therefore prepare for them.
- If we don’t know what to expect, some communities will be very vulnerable when the next big storm hits. (Thinking about Daniel’s paper. He mentioned that the short temporal record of storm tracks meant that some communities weren’t thought of as having a high risk because they weren’t in the historical record).

(Wide Funnel)

- As modeling becomes more advanced from physical exposure data, we need to make sure that human impacts data is collected and made available in a way that matches the physical exposure quality.

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