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’s physical properties. 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 misaligment 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 acheive 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, anenometers, 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 acheive 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 asses 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 acheive 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 thesd 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 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 commmunity infrastructure are damaged, often severly. 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, mortage, 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 or at locations created by models in gridded formations. 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

When we refer to spatial scales, we are referring to the size of a geographic space that data are collected from. In tropical cyclone studies, the size of this space can be as small as a latitude-longitude coordinate (a point location), or as large as an oceanic basin; for example the North Atlantic Basin where North American tropical cyclones typically develop. In general physical exposure data comes from monitors and sensors at point locations, while human impacts data comes from larger aggregated scales such as zip codes, counties, and states.

It can be helpful to think of geospatial data in two major ways, as vectors, or as rasters. Vector data use points, lines, or polygons to represent geographic features and locations (Lovelace, Nowosad, and Muenchow 2019). These vector data are discrete and well-defined, and are typically used to study human impacts, because administrative boundaries and borders utilize this data type (Lovelace, Nowosad, and Muenchow 2019). For example, polygons can be used to represent closed areas such as zip codes, counties, states, countries, islands, or even continents. Tropical cyclone storm tracks can be thought of as as line vectors. Vector points can represent smaller areas such as cities, mountain peaks, locations of hospitals, etc.

The other major spatial data type is a raster. Rasters are gridded data, meaning that they are displayed as cells that divide a surface into equal, regularly spaced parts (Lovelace, Nowosad, and Muenchow 2019). Raster data is often utilized for physical exposures of tropical cyclones because it can display continuous data (such as wind speed or flooding over a geographic area). However, because raster data can also display categorical data, it can also be used for studying human impacts (for example rasterized data could overlay socioeconomic makeup of a city on a map, with each raster representing the dominant group at that location) (Lovelace, Nowosad, and Muenchow 2019).

Here we will describe several spatial scales that are commonly used by researchers studying human impacts of tropical cyclones in ascending order of magnitude. With each scale we will describe how measurements and data are generated from that particular area. We will also describe the methods that researchers use to join physical exposures data with human impacts data to accurately ascertain responses to exposure.

## Vector Data

In tropical cyclone studies, the vector classes most often utilized are self standing point locations, or polygons – which can be thought of as a more complex geometric collection of points.

### Point Location

Point locations are the smallest resolution of spatial data used to assess the exposure to tropical storms and hurricanes. Point locations can be characterized by specific latitude and longitude values, which specify a specific geographic location on a map. Meteorological instruments, monitors, and sensors that collect information on physical exposures are at this spatial level, often located at airports, weather stations, and even personal monitors used by volunteers (example CoCoRAHs).

When Hurricane Ike struck the coasts of Texas and Louisiana in 2008, the U.S. Geological Survey set up 117 pressure transducers (a type of sensor) as a temporary monitoring network spanning over 5,000 square miles along the Gulf Coast of the affected states(East, Turco, and Mason Jr 2008). This temporary monitoring network was designed to record the timing, areal extent, and magnitude of inland hurricane storm surge and coastal flooding.Although the combined network of sensors and the data they record was used to evaluate storm surge models and document the extent of flooding and other site specific effects, each individual pressure transducer represented a specific point location (East, Turco, and Mason Jr 2008).

Storm tracks, which are mapped as lines, are really composed of a series of point locations on a map. These point locations come from known locations based on satellite data or monitors on the ground measuring wind speed, and then the storm track itself is interpolated to visualize the entirety of the track. (Yan et al. 2020) used distance from storm track to assign exposure to the tropical cyclone, and part of the cyclone’s storm track that was closest represented an individual point location. Exposure to tropical cyclones using storm tracks was assessed differently in (Kinney et al. 2008), the storm track simply had to pass through a particular county for residents to be considered exposed, but the storm track itself still represented a series of point locations at every section of the track.

In (Lieberman-Cribbin et al. 2017), a study that looked at associations between flooding and mental health outcomes after Hurricane Sandy struck New York City, residents of areas that experience flooding completed surveys and indicated their street address, city, and zip code. This address information was then geocoded and matched up with the appropriate latitude and longitude and represents data at at point location.

Another example of a study that geocoded physical addresses to use point location data for exposure analysis was (Brunkard, Namulanda, and Ratard 2008). This study analyzed mortality data in Louisiana prior to Hurricane Katrina and characterize deaths related to the storm. Deaths were mapped using the street location where death occurred which were in turn matched with latitude and longitude coordinate systems (in cases where the only address associated with a death was a nursing care facility, the address of the nursing care facility was used).

Point locations represent the smallest spatial resolution of vector data, and the specificity of this small scale can be appealing for getting a close up look at individual human impacts of a tropical cyclone event. However, there are reasons why this spatial scale is not always used, even when it is accessible.

Physical exposure data from point locations is generally reliable and consistent if it comes from monitors and weather stations, but in the case of temporary networks of monitors, as mentioned in the previous example from (East, Turco, and Mason Jr 2008), there isn’t always enough notice and lead time before a storm makes landfall for this to be a reliable and consistent way to measure accurate data.

When using point location and individual level data on human impacts, an important factor to consider is the preservation of privacy. Because health data often contains highly sensitive information about individuals, using point location data can compromise the privacy and even safety of individuals if they are able to be traced to this location. For this reason, even when point location and individual data are available for study of human impacts, the data may be aggregated to a larger spatial level (such as county or state) in order to preserve the anonymity if the individuals.

A real life example to illustrate this point of privacy comes from the Centers for Disease Control and Prevention, which collects data on many different diseases and their outcomes. In the case of arboviral diseases such as Zika, West Nile, Eastern equine encephalitis and many others, data is provided at a spatial level no smaller than the county. Even so, identifiable information such as age, sex, race, and ethnicity is suppressed at the county level if less than three cases were reported in the state in a given year. The main reason for this is to preserve privacy and assure that individuals cannot be identified.

### Polygons - Zip Code/County/Parish/State

While point locations are the most common vectorized spatial scale that physical exposure data are collected at, and human impacts data can also be collected at that level, polygon vectors such as zip codes, counties, parishes, and states tend to be more commonly used for human impacts data. Information on human impacts such as birth outcomes, hospitalizations, tax records, and demographic data are often recorded at this spatial level.

It is important to remember that data at this spatial scale come from individual and point location information at some point in the data collection pipeline, but have been aggregated or deidentified in a way that these invidual and point location data points are no longer apparent. There are a variety of ways that this can be done such as taking an aggregate measuremeant (for example the average birth weight in an zip code), or as a count (such as the total number of hospitalizations in a county). Reasons for making data available at this spatial resolution are often practical (administrative organizations and institutions often collect population level data at this level), but as was mentioned previously it can also be used to preserve the privacy and anonymity of individuals.

In (Huang, Rosowsky, and Sparks 2001), researchers created a damage model from loss information (provided by a large insurer) to estimate damage and losses in coastal zip codes of Florida and the Carolinas due to Hurricanes Hugo and Andrew. The claims ratio (the total number of claims in the code divided by the total number of insurance policies in that zip code), and the damage ratio (the amount paid out by the insurer divided by the total insured value) were compared to the maximum gradient wind speed, obtained from wind field models. The relationships between these ratios and wind speed suggested that when the mean wind speed reached 20 meters per second, structural damage was more likely to occur, and this damage became widespread when mean wind speed reached 30 meters per second (Huang, Rosowsky, and Sparks 2001).

Another example of physical exposures being assigned using polygon spatial scales is FEMA disaster declarations. FEMA disaster declarations are used to determine how much federal aid and funding needs to be allocated to particular regions after a disaster, and in this way can be used to estimate intensity of tropical cyclones and the resulting human impacts on a given area. An example of a study that used this method to assign exposure was (Horney et al. 2021) which looked at the impact of natural disasters on this risk of suicide by identifying counties as exposed if they had a single major disaster declaration between 2003 and 2005.

Another study that looked at human impacts in zip codes is (Lane et al. 2013). A review of the literature as well as using lessons from Hurricane Sandy’s impact on New York City, the researchers mapped population vulnerability indicators in the 42 New York City United Hospital Fund (UHF) neighborhoods, which are zip code aggregated areas located within the city’s five boroughs. In this study, these neighborhoods were characterized by percentages such as percentage of the neighborhood with delapidated or deteriorating housing, percentage of neighborhood’s residents living below the federal poverty line, the percentage of neighborhood residents aged 85 or older, and the percentage of residents with frequent mental distress.

Similar to a county is a parish (unique the state of Louisiana) and was the spatial unit used in (Kinney et al. 2008), which looked at looked at the prevalence of autism following prenatal exposure to tropical cyclones. The study used maps of storm tracks provided by the National Weather Service to identify the parishes that would be most intensely impacted by the storm. A storm track passing through a parish’s boundaries as a proxy for the storm’s intensity in that parish was one of two characteristics that would be used to assign an exposure ranking for residents of that parish (the other characterisitic being how vulnerable to the effects of the storm the residents of the parish would be). Ultimately this study concluded that in Louisiana the prevalence of autism increased significantly in cohorts of children with prenatal exposure to the tropical cyclones.

A study that used the county level to understand the human impacts of tropical cyclones was (Parks et al. 2021). This study, which was concerned with the rate of hospitalizations of older adults in response to exposure to tropical cyclones, assigned the category of “exposed” to counties that experienced or exceed a gale force of greater than or equal to 34 knots. The human impact of concern in this study was quantified using data from enrollees from the Medicare cohort to determine the cause of hospitalization and county of resident. Again, to belabor an earlier point, the enrollees in this Medicare cohort are individuals with residential addresses which could be considered as point locations, that are instead aggregated at the county level to preserve privacy. With the prior knowledge of which counties were exposed to tropical the researchers were able to assign exposures to these residents.

Spatial scales larger than point locations, zip codes, and counties are the state and national levels of studying human impacts of tropical cyclones. This spatial scale is not used as often but when it is it 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.

Another study that used the spatial scale of state to study the human impacts of tropical cyclones was (Grech and Scherb 2015), which showed that in utero exposure to Hurricane Katrina (exposure assigned by measuring the amount of rainfall after the storm in the Gulf states) had an impact on the difference of survival of male and female fetuses, which later impacted the male/female birth ratio at the end of the pregnancy. Data on male and female live births was taken from the Centers for Disease Control and Prevention on a monthly basis at the state level from Alabama, Florida, Louisiana, and Mississippi. Rainfall as a metric of exposure to Hurricane Katrina was also analyzed at the state level, presented in inches for each state in the three days that Hurricane Katrina struck the Gulf Coast.

## Rasterized Data

Where vectorized geographic data objects can delineate boundaries and precise locations on a map, rasterized data can fill in the space and create a continous picture that shows variation across a geographic space. Rasterized surfaces are created using gridded networks and modeling.

For example, in (Anderson et al. 2020), rainfall was used to assess exposure to tropical cyclones by summing hourly precipitation measurements from the North American Land Data Assimilation System Phase 2 (NLDAS-2). This network spans the continental United States at 1/8∘ grid points. In this study the precipitation data from this grid was used to create a daily precipitation total for each grid point, then the gridpoints in a county were averaged together (based on counties’ 1990 Census boundaries), which then created a daily county level estimate of precipitation for each U.S. county from 1988-2011.

In (Anderson et al. 2020), a wind-based exposure metric was also used; the county-level peak sustained surface wind during each storm.To do this, the 1 minute surface wind was modeled at each county’s mean population center.

# Temporal Scales

Thanks to scientitific 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.

When thinking about temporal scales in tropical cyclone studies, it is useful to think of them either as snapshots in time, or as cumulative measurements up to a specific time. To illustrate this point, snapshots in time can be thought of as thermometers. Thermometer measurements represent the temperature at a specific point in time, and do no show what the temperature was previously. In contrast to this, cumulative measurements are the types of measurements taken by rain gauges. A rain gauge collects and measures the amount of rain water gathered over a specified duration of time, thus it is not a snapshot at all, but in fact a cumulation. These two modes of thinking about temporal scales will guide the way that we discuss the scales below.

## Snapshots of Time (The Thermometer Model)

Just as spatial scales exist at different levels (point location, zip code, county, etc.), so do the temporal scales of time snapshots. The difference here is that these time scales exist as frequency of snapshots at the level of minutes, hours, days, etc. Here we discuss how tropical cyclone studies utilize snapshots at different temporal scales, because how often measurements are taken is important for understanding what the data can and cannot tell us.

Relatively short intervals of time such as minute or hourly snapshots are possible for many physical exposures because weather monitiors and stations can easily record this information at consistent and regular frequencies. Because the snapshots are taken at such regular intervals, they can be used to construct continuous estimates of other storm properties such as the storm track. The storm track itself is constructed by stringing together measurements of wind speed and other properties at a specific time and place. If a hurricane is tracked at intervals of every 6 to 3 hours, this can also be interpolated to estimate location at more regular intervals, for example every fifteen minutes.

The sensors that were previously mentioned in (East, Turco, and Mason Jr 2008) are an example of a study that used this type of time scale. The storm surge and inland flooding caused by Hurricane Ike were calculated by these deployed pressure transducers which took measurements of surge pressure, barometric pressure, and temperature every minute. The key point here is that these snapshot measurements taken by the pressure transducers represent the a property of the storm surge or flooding at a single moment in time.

(S. Grabich et al. 2016) used storm track data from the National Oceanic and Atmospheric’s Association to compare disaster exposure assignment to FEMA presidential disaster declarations. The data used to construct NOAA’s storm tracks records the magnitude and geographic location of the storm every 6 hours, and each of these 6 hour measurements is a single snapshot of where the storm center is in time and space. (Anderson et al. 2020) also used storm tracks to generate a distance-based exposure metric, and they interpolated the tracks to get storm track locations at every 15 minutes. Even though these interpolated values are estimates created from a model, they still represent snapshots of the time and location of the storm center, but at a much finer scale.

Measurements of human impacts are not available as often at such fine temporal scales, although there are certainly certain measurements that could be taken, for example the timing of phone calls to emergency departments or more recently by social media posts that pertain to the storm.

Some snapshot measurements are taken at intervals that are much larger in temporal scop than minutes or hours, for example on the time scale of days and weeks. Because physical exposure data is so easily recorded at fine temporal resolutions, snapshots that are taken at more daily or weekly frequencies are often associated more with human impacts. Daily or weekly summaries of abseentism at work or school due to inclement weather conditions are an example of snapshot data taken at this level.

(Parks et al. 2021) is an example of a study that took daily measurements to study human impacts of tropical cyclones, in this case daily hospitalization rates. The study used a conditional quasi-Poisson regression model to analyze the daily hospitalization rate up to 7 days after the day of hurricane exposure. Hospitalizations from respiratory diseases and from injuries increased all days after the day of exposure, peaking on the first and second days respectively. For several other causes of hospitalization such as cardiovascular disease, endocrine disorders, genitourinary diseases, infectious and parasitic diseases, nervous system diseases, and skin and subcutaneous tissue diseases, the rate of hospitalization decreased on the day of exposure to the hurricane and then peaked about 1 to 3 days later before returning to the expected rate before the storm (Parks et al. 2021). The daily number of hospitalizations represents a snapshot because it is a slice of time and doesn’t tell us about the total and final number of hospitalizations resulting from the entire storm.

Zooming out to even broader time scales, snapshots can be taken at seasonal, yearly, or even decadal frequencies. Once again this will also be associated more strongly with human impacts. For example, the U.S. Census occurs every 10 years and is acts as a proxy for a snapshot of the nation’s population. These 10 year snapshots can reveal changes in population, socioeconomic status, and other information in regions affected by tropical cyclone events.

In the study (Jaycox et al. 2010), mental health outcomes of New Orleans school children was assessed 15 months after Hurricane Katrina, and an intervention strategy was implemented to help treat these outcomes. The children were assessed for symptom of post traumatic stress disorder and depression first at baseline (December 2006/January 2007), again 5 months after intervention, and then again 10 months after intervention. Overall the treatment was shown to reduce symptoms of PTSD, although this was not even across all groups.

***Try to think of an example of snapshots that would be taken on an annual basis***

### Cumulative Measures Over Time (The Rain Gauge Model)

Cumulative measurements within a defined period of time give different information about exposures and impacts of tropical cyclones. Instead of giving information about a precise moment, cumulative measurements inform researchers on the amassed value of a specified measurement, in other words everything up to a certain point. Rain gauges are an effective way to visualize cumulative data because the measurement reflects the total amount of rain water that has been collected in a designated period of time. The final volume of the rain gauge is not a snapshot, as an specific quantity like 3 inches of rain doesn’t exist all at once, but instead it shows the additive amount that has occurred in a known time frame.

Similar to the way that snapshot measurements can be recorded at varying intervals of time, cumulative data can represent total measurements over varying spans of time. Cumulative measurements of physical exposures will often be taken over smaller periods of time, on the order of minutes, hours, or days which corresponds to the lengths of the storms themselves. Over a the span of several hours or several days such measurements as the total amount of rainfall, or the number of minutes where wind exceeded a certain speed could come to represent cumulative measurements on a smaller scale. Cumulative measurements that give information on human impacts typically happen on the order of days, weeks, months or years. Daily and weekly counts of deaths and hospitalizations in an area due to the effects of tropical cyclones are cumulative measurements. Over the span of months and years, cumulative measurements of human impacts could encompass things like the total dollar value of insurance claims in a particular neighborhood struck by flooding, or the net migration of people in or out of a community after the impact of a storm.

Many cumulative measurements are taken of human impacts of tropical cyclones simply because there is no way to measure certain impacts at a precise moment or in the midst of the storm, so damages and impacts have to be assessed once the storm has passed. It is also important to note that snapshots and cumulative measurements are not always so clearly separated. A daily count of hospitalizations could reflect the cumulative number of patients hospitalized (imagining them all in a rain gauge together), or it could represent a snapshot of how many people have been hospitalized at a precise moment.

# Implications of not improving this integration

Temporal and spatial misalignment poses certain challenges to researchers investigating the human impacts of tropical cyclones. Integrating data at different spatial scales is often accomplished by aggregating one set of data to match the data that is at a greater scale. Sometimes however, misalignment exists not at different scales, but at the same scale in different places, such as a residence that is miles away from the nearest weather monitor. In cases such as this, physical exposure is assigned by matching residences or addresses to the nearest monitor, or an interpolation model will be created to estimate exposures. In the following sections we will discuss aggregation and some of the implications that arise from it. We will then describe matching and interpolating and similary describe the implications that result from these methods.

## Aggregating to Integrate Data at Different Scales

Aggregating physical exposures is what researchers do by assigning a single exposure value to a wider spatial area, such as a zip code or county. Since the human impacts data available will often be at this scale anyways, the finer physical exposure data will be generalized to this level as well. This can be done in a number of ways, such as taking a wind speed measurement from a monitor at the center of the county. This wind exposure value will then be assigned to the entire county. Windspeed at the moment a tropical cyclone makes landfall is another exposure assignment method, as was done in (Shao et al. 2017), in which the maximum wind speed when a tropical cyclone made landfall in a particular coastal county was used to assign that particular county’s exposure. Cumulativie rainfall in the entire county, distance of the county from the storm track, number of tornadoes in the county, and floodindg in the county are other methods of assigning an aggregate exposure value to a certain region.

It is often the case that these aggregated values will be determined to categorize a county or other spatial area as exposed or unexposed, based on some kind of threshold. In (Parks et al. 2021), researchers considered counties exposed if the peak sustained wind that day exceeded a gale force greater than or equal to 34 knots on the Beaufort scale when the cyclone was at the point of closest approach to the county. Entire counties will also be categorized as unexposed or exposed based on whether the storm track of the tropical cyclone passed through their borders or not.

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.

### Implications of Aggregating Data

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 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 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.

### 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 track got close 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.

####[Need to figure a way to conclude this section]####

## 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, sometimes in regular grids, but the human impacts point locations could be tied to a single residential address that is likely not at a weather station or in a grid.

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.

Another method of assigning exposure to spatially misaligned individuals is to interpolate, using models. 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.

A limitation of both matching physical exposure monitors to residences, and using interpolation models to infer exposure values, is that meteorological events can damage these monitors. Strong storm events that produce high enough winds can blow away or damage senors. If precipitation is being measured, rain that comes down in slants can also make measurements less accurate. These are issues that are particularly concerning for ground based monitors.

The more complicated that a model becomes, the harder it is to interpret. This is why the most simple method that can be utilized (sometimes simply matching human point locations to the nearest monitor) is the best way to go. Some exposures, like wind speed, are relatively homogenous over large areas, so the different methods will not give much variation in results.

### 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.

# 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. These differences in temporal and spatial scale make use of the data difficult for researchers to immediately utilize. Nevertheless, several methods exist for integrating these datasets, and we’ve briefly described aggregation, interpolation, and matching as the main methdos for doing this. Though useful, these methods are not without their limitation, such as their propensity towards ecological bias and exposure misclassification.

Ecological bias and exposure misclassification are a problem, because they impact the external validity of tropical cyclone studies. If not adequately mitigated, they can produce measures of association that do not reflect the true impact that tropical cyclones have on coastal communities. In other words, these kinds of bias and error make tropical cyclone studies less generalizable, which renders them less effective in predicting for future events and preparing for them. That leaves large gaps of uncertainty when it comes to creating resilient communities that can withstand tropical cyclone events, and leaves more vulnerable populations and communities at an elevated risk. [Cite Daniel’s paper]

There is reason to be optimistic that we can harness the power of large datasets on physical, and increasing precision in model building, to understand and predict the effects of tropical cyclones on human health, economic viability, infrastructure, and social dynamics. This is of course contingent on our ability as researchers to make sure that the data on human impacts is of a similar quality and translatable resolution as the high quality data we already have on physical exposures. With larger populations expected to live in areas threatened by tropical cyclones in the future, this is an extremely important undertaking for interdisciplinary teams of meteorologists, epidemiologists, economists, and diaster planners.

Link to online book Geocomputation in R <https://geocompr.robinlovelace.net/> # References

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