Assessing exposure to Atlantic Basin tropical storms in United States counties

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Abstract

There are many important applications for having county-level estimates of exposure to tropical storms over many years. For example, … . Current approaches include … but have the following limitations … .

Here, we present open source software we have developed to explore county-level exposure to tropical storms in United States counties between 1988 and 2011. Further, we explore the differences in exposure classification when using different metrics (e.g., wind speed, rainfall, distance).

Introduction

What it means to assess county-level tropical storm exposure.

Why it's important to measure TS exposure for counties. Many outcomes of interest are available at county-level aggregations (e.g., counts of health outcomes: Grabich et al. (2016): premature births and low birth weights). Further, decisions and policies to prepare for and respond to storms are often undertaken at the county level (Zandbergen 2009). Some studies suggest methods to determine exposure, including inland exposure, to tropical storms at the county-level over many years (Zandbergen 2009). Here, we offer tools, through the open-source `hurricaneexposure` package, to determine county-level exposure to tropical storms using several different metrics (distance, rainfall, wind). In this paper, we describe how this software package assesses exposure to tropical storms at the county level, provide an analysis of the advantages and disadvantages of different strategies for assessing county-level exposure, and explore variation in exposure assessments based on using different exposure metrics.

Current hurricane exposure assignments are often nonspecific [GBA– I found this wording a bit unclear] and may lead to missclassification of exposure at the county-level (Grabich et al. 2016). Researchers have found heterogeneity in exposure assignments of counties, both within and between storms, when different metrics of exposure are used (Grabich et al. 2016). Such missclassification can have important implications of assessments of the public health and economic impacts of tropical storms.

Many of the studies that have assessed exposure to tropical storms in the US have used geographical information system software (e.g., ArcGIS) [example studies]. Here, we offer methods to map and output historic exposure to tropical storms that does not require the use of proprietary software but instead uses a package written in the R statistical programming language, which is free and open-source.

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Examples of estimating TS for multiple storms. When assessing exposure to a single tropical storm, a detailed analysis of ... can be performed for the storm. However, this level of detailed analysis is unreasonable when assessing exposure to all storms over an extended time period; further, such a long-term exposure assessment requires consistency in the data being used to determine levels of exposure to factors like wind and rain.

A few studies have sought to determine exposure to tropical storms over a study period that includes multiple storms. For example, ... assessed the exposure of counties in Florida to hurricanes during the 2004 season [citation]. The largest county-level exposure study is likely that of Zandbergen (2009), which estimated exposure in US counties to all [US landfalling? or all storms?] Atlantic basin tropical storms between 1851 and 2003, using both distance and an exposure metric that incorporated distance and windspeed. They used this exposure evaluation to create maps of total exposure to tropical storms within US counties, as well as to explore associations between a county's long-term exposure to tropical storms and its location, distance from the coast, size, and shape (Zandbergen 2009).

Examples of other datasets at the county level. If exposure to tropical storms over multiple storms and years can be assessed, these exposure datasets can be joined with other time series to explore the impacts of tropical storms. For example, daily counts of human health outcomes in environmental epidemiology studies are often available aggregated at the county level, and such data has often been paired with time series of environmental exposures (e.g., air pollution, temperature) to determine associated risks.

Data and Methods

Distance-based exposure. We collected "best tracks" data on hurricane tracks for Atlantic basin storms between 1988 and 2014 from the extended best tracks database. This dataset is based on a poststorm assessment of each storm conducted by the United States National Hurricane Center (NHC) and incorporates data from a variety of sources, including satellite data and, when available, aircraft reconnaisance data (Landsea and Franklin 2013). This data gives time stamps for each observation in Coordinated Universal Time (UTC; also known as Zulu Time, sometimes indicated by "Z").

These data typically give measurements of storm center location at 6-hour intervals, at synoptic times (i.e., 6:00 am, 12:00 pm, 6:00 pm, and 12:00 am UTC); some landfalling storms have an additional observation at the time of landfall (Landsea and Franklin 2013). These positions are given to within 0.1 degrees latitude / longitude at these synoptic times (Landsea and Franklin 2013). We interpolated these location values to every 15 minutes during the period when the storm was active, using a linear interpolation between each measured point.

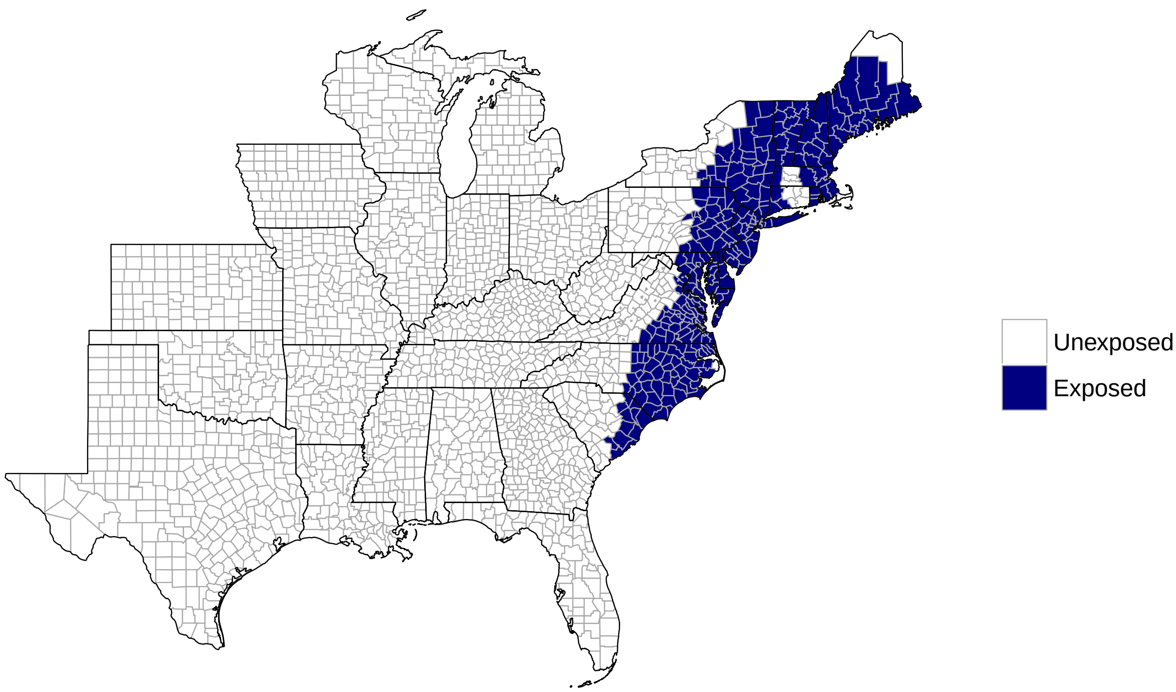
We calculated the distance between each county's center and each of the 15-minute-interval estimates of a storm's location. To do this, we used the Great Circle method to calculate the distance between pairs of latitude and longitude coordinates, using the R package `sp`. For each county, we used the population mean center, based on the U.S. Census's 2010 Decennial Census, as the center location of the county. From these distance calculations, we identified the date-time and distance between the storm track and the county center at the 15-minute interval when the storm was closest to the county center. We used the `countytimezones` R package to convert each date-time of the closest storm approach for a county to the county's local time zone and identified the local date when the storm was closest to the county. This "closest date" was used to pair the distance estimates with rainfall estimates.

Rain-based exposure. Given its high resolution and consistancy with rain gage values, (Villarini et al. 2011) recommends the use of Stage IV precipitation data for the analysis of rainfall distribution in landfalling tropical cyclones. However, the Stage IV dataset only provides data since 2001 (Lin and Mitchell 2005) and is therefore inadequate for use in this analysis.

NLDAS does not provide information on precipitation over the ocean, preventing its use in assessing the develpment of the storm prior to landfall (Villarini et al. 2011). This point is moot for this analysis.

Wind-based exposure. These wind models use estimates of maximum wind speed from the best tracks dataset. These maximum wind speed estimates in the best tracks dataset are rounded to 5-knot intervals and is the maximum 1-minute-average windspeed at 10 meters above the ground (Landsea and Franklin 2013). This windspeed is typically determined using the Dvorak technique to estimate windspeed from satellite measurements, although data from aircraft reconnaisance in also sometimes incorporated in the estimate (Levinson et al. 2010).

Results



Discussion

Distance-based exposure. There are some sources of uncertainty for storm locations from the best track hurricane data. These include . . .

However, these best tracks should be fairly reliable for more recent years of storms, as we use here. Many of the uncertainties related to storm positions in best track data are more of a concern for the years before . . . (e.g., pre-19[xx]).

While there are often several different "best tracks" datasets, from different sources [?– weather services?] for other ocean basins, the "best tracks" data from . . . , which is the basis of the tracks we use here, are the undisputed primary source of tropical storm track data for the Atlantic basin.

There are a number of limitations to using distance to assess exposure to tropical storms. Tropical storms vary in size and intensity, and a measure of distance from the storm track will not incorporate these differences and so could misclassify exposure both in terms of generating false positives (counties close to the storm track of very mild or small-radius storms) and false negatives (e.g., during very large or intense storms). In particular, the forces of a storm tend to be distributed around the center in a non-symmetrical way [citation], while distance-based exposure metrics that use buffers tend to use an equal buffer distance on each side of the storm track (e.g., [citations]).

Other distance-based exposure metrics have defined "exposure" to occur only when a storm's center track passes through a county's boundary (e.g., Zandbergen (2009), who describe this metric of exposure as a "hit" on the county). This way of measuring exposure can exclude nearby counties that suffered extreme conditions from the storm but were not directly on the hurricane's track, especially since hurricanes can have a width ([typical storm width; citation]) that is much larger than a typical county's width. Further, exposure assessed using this method has been found to be significantly [? double-check] associated with the size and shape of a county (Zandbergen 2009). By contrast, assessing distance-based exposure based on measuring distance between the storm track and each county's center would be less susceptible to differences in county size and shape and so might be a more reliable metric of exposure than determining if a storm track ever crossed a county boundary. Further, assessing the minimum distance between county center and the storm track, as we do here, allows for a continuous, rather than binary, metric of distance-based exposure to a storm.

The Zandbergen (2009) study assumed symmetrical activity of storm related factors,which does not accurately represent storm characteristics once landfall has been made (Kruk et al. 2010, Halverson (2015)) [GBA– I did not understand this thought. I agree that storms are asymmetric, but I don't think that's just after landfall. Is this something about characteristics of storms as they transform to extratropical systems? Let's discuss.]

There is some uncertainty in the position estimates from the best tracks hurricane dataset, since the estimation of storm position for best tracks data involes a poststorm subjective smoothing and integration of many different types of data (Landsea and Franklin 2013). In a survey of researchers who perform the poststorm data aggregation to create the best tracks datasets, uncertainty in the center position of a US landfalling storm in the "best tracks" dataset was estimated at approximately 8 nautical miles for major hurricanes, 11 nautical miles for Category 1 and 2 hurricanes, and 15 nautical miles for tropical storms (Landsea and Franklin 2013). Uncertainty in estimates of a storm's position also varies by time of day, with more certain estimates during daylight than during the night (Landsea and Franklin 2013).

Currently, distance parameters involved with assessing risk of a particular storm have been rather arbitrary, contributing to the necessity in understanding how such parameters influence a county's exposure status. In assessing the risk of a given storm based on distance, recent studies have defined the distance from the storm track affected by a given storm differently. (Czajkowski, Simmons, and Sutter 2011) assessed county-level risk and exposure based on a three-tierd definition, with primary counties being those closest to the storm track on either side, secondary counties being adjacent to primary coutnies, and tertiary counties adjacent to secondary counties. Such a definition resulted in an exposure defenition based on an average distance radius of 120 km on either side of the storm track (Czajkowski, Simmons, and Sutter 2011). Such a distance is slightly greater than that commonly used by public health departments (i.e., 100 km) (Czajkowski, Simmons, and Sutter 2011).

Another study used distance buffers of 30, 60, and 100 kilometers for different metrics of distance-based exposure (Grabich et al. 2016) [check the paper– was this distance to any part of a county, or to the center of the county?].

In a study assessing the association between hurricanes and undesireable birth outcomes, researchers found that results were not sensitive to the omission of residences 100 km from the storm path, and that results varied insignificantly from 30-75 km (Currie and Rossin-Slater 2013).

Rain-based exposure. It can be very difficult to reliably measure rain during extreme rain events, including tropical storms. For example, a heavy rain can wash away [?] rain monitors [?]. It can also be very hard to measure rain during heavy wind, as the rain does not fall straight into the monitor [?].

Some of the other possible sources for estimating rain during tropical storms include . . . [Stage IV, TMPA, NEXRAD]

The estimated rainfall amounts from our data are likely underestimates. This data source, however, should be internally consistent and so useful for comparing across different storms when all exposure estimates are based on this rain data.

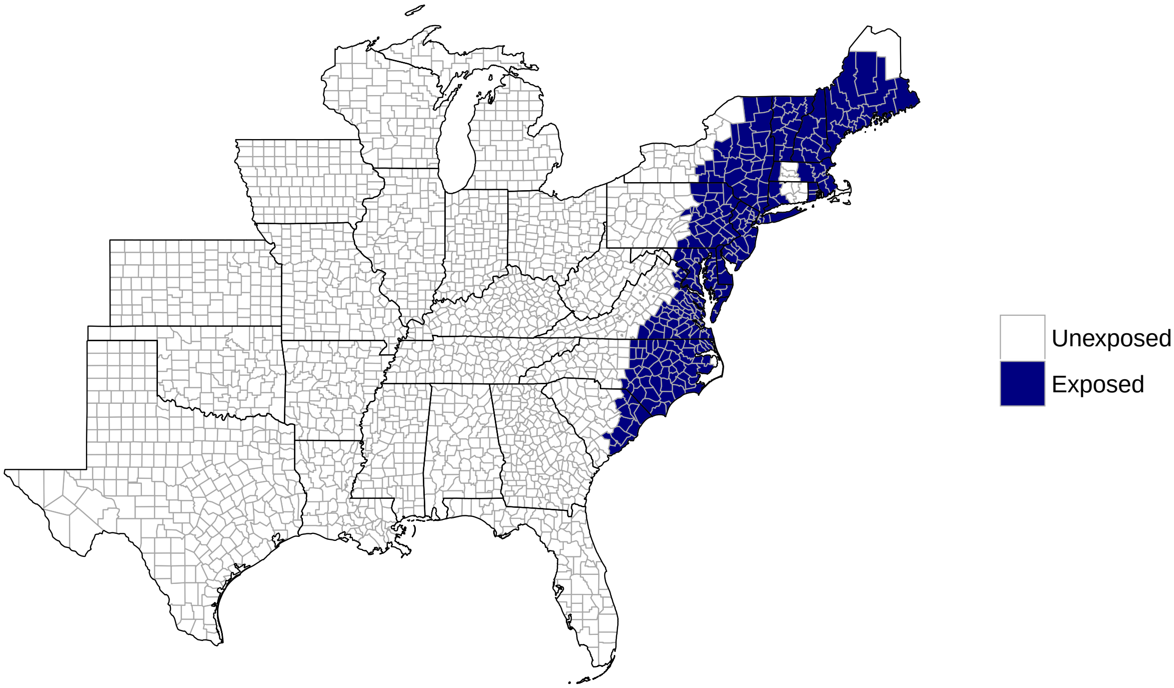
Rainfall estimates are likely underestimates for a few reasons. First, they are based on averaging hourly measurements to a daily mean estimate. This averaging would smooth over shorter periods of very extreme rainfall. Further, this data is averaged over multiple grid points within each county and so would not fully reflect very extreme local precipitation (although this might be less of a concern for classifying exposure to a large-scale storm system, like a tropical storm, compared to more fine-scale storms). Finally, this NLDAS data provides a re-analysis that incorporates measured rainfall, using models, etc., to incorporate that observed data into a spatially and temporally continuous dataset of rainfall. However, during extreme storms, the problems with measuring rainfall using [rain monitors] would propogate into the NLDAS data, so although NLDAS would prevent missing values during the storm if monitors are not able to provide data, if monitors are out, rainfall estimates from NLDAS will be based more on models than on observations. More on NLDAS bias low here (Villarini et al. 2011). Such bias, though unimportant in our analysis, may play a larger role in the extrapolation to other studies or exposure analysese where the precipitation cutoffs used here may provide a threshold that results in the missclassification of less affected counties as exposed.

Exposure classification based on rainfall has some advantages. For example, it allows the identification of exposed counties that are inland, rather than coastal, but that were affected by heavy rainfall during the storm. Often, storm-related deaths are associated with inland flooding. In fact, over half of the hurricane-related fatalities from 1970 to 1999 were a result of freshwater flooding, accounting for the vast majority of deaths in inland counties (Rappaport 2000). In another analysis, researchers found that 79% of freshwater-drowning fatalities occured in inland counties,(Czajkowski, Simmons, and Sutter 2011) further stressing the importance of rainfall in hurricane risk analysis. Storms can produce a lot of rain especially in certain topographies, like near mountains, so counties that are well inland can sometimes experience more extreme rain that other counties at similar distances from the storm's track.

In comparison to the storm track, the areas of extreme rain and extreme wind can vary. For example, storms undergoing an extratropical transition can bring heavy rains to the left of the storm's center track, while extreme winds are more common to the right of the track (Halverson 2015, Grabich et al. (2016) GBA– I think it would be better to just use meteorological papers as references for this point. The Halverson paper is great, but the Grabich paper I think might just be a secondary, rather than primary, reference for this point, so I think we could probably find a more direct reference). Wind speeds are typically more severe to the right of the storm's track because here the counter-clockwise cyclonic [right word?] winds are moving in the same direction as the forward motion of the storm, creating an additive effect for total windspeeds [citation]. In contrast, rains can be heaviest to the left of the storm's track, especially in cases when the storm interacts with a downstream ridge (Atallah, Bosart, and Aiyyer 2007).

Some storms can be of lower intensity (i.e., on the Saffir-Simpson scale) yet bring dangerous rainfall, including well inland of the storm's landfall. For example, storms including Floyd in 1999, Gaston in 2004, Irene in 2011, and Lee in 2011, have had severe inland impacts, often through extreme rainfall, as post-tropical storms (Halverson 2015). This rainfall can be particularly severe in the Appalachians (Halverson 2015). Further, heavier rainfall is more common for storms moving at slower forward speeds (Chang, Yang, and Kuo 2013). Storms with a slower forward speed and larger rainfall area contribute to a longer duration of rainfall, and therefore an increased chance of flood-related damage (Rezapour and Baldock 2014).

For example,



Wind-based exposure. Wind suffers from similar challenges for measuring during tropical storms. In particular, the strong winds of tropical storms can break or blow away the anemometers used to measure wind speed.

Here, we used wind speed models, rather than observed wind speed, to estimate exposure to tropical storms based on winds.

A variety of other wind speed models exist besides the one used here. In particular, there are options for wind speed models as far as ... One study used a very simple model of constant winds up to a distance of 30 km from the storm track and a simple model of wind decay beyond that distance (Zandbergen 2009), based on a model developed by ... [see references for this paper]. Another study used wind data from a NOAA public database based on real-time hurricane wind analysis, rather than modeling windspeeds themselves (Grabich et al. 2016) [see the Powell reference in this paper for more on that data].

There is some uncertainty in the maximum wind speed values estimated at each synoptic time for each storm. For US landfalling storms, the estimate of storm intensity in the best tracks dataset is estimated to have an uncertainty of around 8 knots for tropical storms, 10 knots for Category 1 and 2 hurricanes, and 13 knots for major hurricanes (Landsea and Franklin 2013). Since the wind model used here uses these best tracks maximum wind speeds as an input, this uncertaintly would propogate into our estimates of windspeed within each county for each storm.

A recent study suggests that nearly all states east of the Rocky Mountains have experienced wind exposure associated with either tropical or post-tropical storms (Kruk et al. 2010).

Exposure metrics based on wind speed may not provide an accurate representation of the communities exposed to a given storm, since, while wind speeds rapidly decay after landfall [citation], extreme rain can persist,for some storms affecting a large number of inland counties, which would be underrepresented using an exposure metric the depends on windspeed.

Examples of studies that used windspeed as a sole criteria when determining tropical storm exposure include ... [citation]. In other studies, wind criteria have been combined with distance criteria, and with windspeed modeled based on maximum sustained windspeed estimates at each "best tracks" observation, combined with a simple model of decay in wind speed at distances further from the storm's center (wind speed equals the storm's maximum sustained windspeed up to 30 kilometers from the storm's center then follows a simple decay function beyond that distance) (Zandbergen 2009) [GBA– this paper references another paper with more details on this decay model for windspeed– the Gray and Klotzbach reference they have]. In this study, wind speed cutoffs of 40 mph, 75 mph, and 115 mph were used to determine if a county was exposed to a storm (tropical, hurricane-force, and intense hurricane-force, respectively) (Zandbergen 2009).

One study found that using a distance-based exposure metric that required the storm track to cross a county boundary assessed a number of counties as "unexposed" that suffered tropical storm- or hurricane-force winds from the storm and were assessed as "exposed" using a metric that combined distance and windspeed (Zandbergen 2009); in fact, almost twice as many counties were assessed as having been exposed to at least one tropical storm between 1851 and 2003 when exposure was determined based on a combined wind-distance metric compared to a "hit" distance-based metric (Zandbergen 2009). This suggests that some distance-based metrics might result in a number of false negatives for county-level storm exposure.

Studies that have used wind-based exposure metrics have used a variety of windspeed cutoff values to determine exposure. One study, for example, assigned a binary exposure value based on windspeed thresholds of 63 and 119 kilometers per hour, as well as a continuous exposure metric based on the exact value of the windspeed in the county during the storm and a categorical exposure metric based on the Saffir-Simpson storm severity categories (Grabich et al. 2016).

Other ways of assessing tropical storm exposure. One study used FEMA disaster declarations as a binary indicator of tropical storm exposure (Grabich et al. 2016). They found that this metric tended to assess a lot more counties as "exposed" to a storm than distance- or wind-based metrics (Grabich et al. 2016), although they only compared the two exposure metrics as applied to four storms (Hurricanes Charley, Frances, Ivan, and Jeanne in Florida in 2004).

Example uses of exposure datasets.

Table including various exposure papers and the parameters used.

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