**Title:** Assessing United States county-level exposure for research on tropical cyclones and human health

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**Abstract**

**Background:** Tropical cyclones bring severe impacts to U.S. communities, including substantial human health risks, from hazards that include wind, rain, flooding, and tornadoes. However, studies quantifying tropical cyclone risks and impacts vary widely in how they classify exposure to tropical cyclones, using various hazard-based metrics and, in some cases, using distance from the storm track as a surrogate.  
**Objectives:** (1) Investigate how well county-level assessments of tropical cyclone exposure agree when based on distance versus hazard-based measurements, as well as among assessments based on different hazard measurements, and (2) provide software to improve tropical cyclone exposure assessment for health-related research.  
**Methods:** We measured county-level exposure to tropical cyclones in the United States based on distance from the storm track, maximum sustained wind, rainfall, flooding, and tornadoes for all land-falling or near-land Atlantic basin storms, for 1996–2011 for all metrics and up to 1988–2015 for specific metrics. We quantified how well county-level exposure assessment agreed for all pairwise combinations of metrics.  
**Results:** In most of the storms investigated, agreement in county-level exposure assessment was at best moderate, and often poor, when using distance compared with four hazard-based measurements. There was also substantial disagreement in exposure assessment based on all pairwise combinations of the four hazard-based measurements. There were geographic patterns in exposures based on these metrics, with most wind-based exposures near the coast, flood- and rain-based exposures extending to inland and northern counties, and tornado-based exposures in southern counties.  
**Discussion:** Our results suggest that when impact studies use distance as a surrogate for tropical cyclone exposure, or use one hazard-based metric when the impact is partly or fully caused by a different hazard, the study will be prone to exposure misclassification. To facilitate future research, we make this multi-hazard storm exposure data available through open-source software.

**Introduction**

Tropical cyclones, including hurricanes, can have disastrous impacts in the United States (U.S.). A tropical cyclone’s high winds can bring health risks and property damage through structural damage of houses and other buildings, falling trees, and wind-borne debris (Rappaport 2000). Storm winds can also cause power outages (Liu et al. 2005, Han et al. 2009), which introduce a number of threats to human and ecological health, including water quality risks if the outage affects wastewater treatment plants (Mallin and Corbett 2006). Other risks can exist without severe wind; for example, one study found that most of the direct hurricane-related deaths in the U.S. between 1970 and 1999 occurred in cases when wind was below hurricane strength, including for Tropical Storms Charley in 1998 and Alberto in 1994 (Rappaport 2000). Tropical cyclones can produce excessive rain, especially in certain topographies (e.g., near mountains), so counties well inland sometimes experience more extreme rain than coastal counties. Flood risks from tropical cyclones can result from this rain, although the two risks are not perfectly correlated (Chen et al. 2015). In the U.S., over half of hurricane-related direct deaths from 1970 to 1999 from Atlantic basin storms were a result of freshwater flooding (Rappaport 2000). Flooding can also degrade water quality (Mallin and Corbett 2006), which can threaten both human and ecological health.

To measure tropical cyclone exposure for either investigations of exposure patterns or for estimation of tropical cyclone risks and impacts, including those related to human health, studies have varied widely in how they determine tropical cyclone exposure (some examples shown in Figure S1). While some studies have measured exposure based on specific hazards of the tropical cyclone (e.g., wind, rain), many have used distance from the tropical cyclone’s central track as a surrogate in identifying exposure to the hazards of a tropical cyclone (e.g., Czajkowski et al. (2011), Tansel and Sizirici (2010), Kinney et al. 2008, Caillouët et al. (2008)).

Distance from the tropical cyclone’s central track can be easily measured using widely-available hurricane tracking data. There are, however, a number of limitations to using distance to assess exposure to tropical cyclones, and there are reasons to suspect that exposure classifications based on other tropical cyclone hazards may disagree with distance-based classifications. Tropical cyclones vary dramatically in size: U.S. tropical cyclones have been observed with radii to maximum winds as small as 20 kilometers and as large as 200 kilometers (Mallin and Corbett 2006, Quiring et al. 2011). While a number of tropical cyclone hazards are strongly associated with distance from the tropical cyclone’s center (e.g., wind and, at the coast, storm surge and waves (Rappaport 2000; Kruk et al. 2010)), other hazards like dangerous rain, floods, and tornadoes can occur well away from the tropical cyclone’s central track (Rappaport 2000, Atallah et al. 2007, Moore and Dixon 2012). For example, fatal tropical cyclone tornadoes, which were linked to over 300 deaths in the U.S. between 1995 and 2009, most often occur 200–500 kilometers from the tropical cyclone’s center (Moore and Dixon 2012).

Further, distance-based exposure metrics that use buffers tend to use an equal buffer distance on each side of the tropical cyclone track (e.g., Czajkowski et al. (2011), Grabich et al. (2015), Grabich et al. (2016), Zandbergen (2009), Tansel and Sizirici (2010)), but the forces of a tropical cyclone tend to be distributed around the center in a non-symmetrical way. For example, extreme winds are more common to the right of the track, where counter-clockwise cyclonic winds move in concert with the tropical cyclone’s forward motion (Halverson 2015), and the fatal tornadoes associated with U.S. tropical cyclones between 1995 and 2009 occurred almost exclusively to the right of the tropical cyclone’s track, mostly in the right front quadrant of the tropical cyclone (Moore and Dixon 2012). Rain, conversely, is often heaviest to the left of the tropical cyclone’s track, especially when the tropical cyclone interacts with other weather systems (Atallah and Bosart 2003, Atallah et al. 2007, Zhu and Quiring 2013) or undergoes an extratropical transition (Elsberry 2002).

The use of different exposure metrics across studies hampers the development of a scientific consensus on tropical cyclone-related risks, as differences observed between studies could result from differences in exposure assessment. Further, if a study misclassifies exposure to the hazard or hazards that cause an impact, estimates of tropical cyclone risks or impacts will be biased, making it hard to identify true associations. These concerns are particularly important if there are large differences in the locations that are determined to be exposed based on different metrics.

To investigate this, we measured county-level exposure to tropical cyclones in all eastern U.S. counties using five metrics (Table 1): (1) distance to tropical cyclone track; (2) maximum sustained wind speed; (3) cumulative rainfall; (4) flood events; and (5) tornado events. We assessed exposure at the county level since data on many potential impacts are available at county-level aggregations (e.g., direct hurricane-related deaths (Czajkowski et al. 2011); birth outcomes (Grabich et al. 2015, Grabich et al. 2016); autism prevalence (Kinney et al. 2008)) and since decisions and policies to prepare for, and respond to, tropical cyclones are often undertaken at the county level (Zandbergen 2009, Rappaport 2000). We explored patterns in these exposure assessments and measured how well exposure classification agreed across these five metrics in terms of classifying specific counties as exposed to a tropical cyclone. Finally, to make this hazard-specific tropical cyclone exposure data available to other researchers, we published open source software for county-based hurricane exposure assessment in U.S. counties (Anderson et al. 2017c).

**Methods**

All counties in the eastern half of the U.S. (e.g., Figure 1), as of the 2010 U.S. Decennial Census, were included in the study. The study covered all tracked storms in the revised Atlantic hurricane database (HURDAT2; Landsea and Franklin (2013)) that came within 250 kilometers of at least one study county between 1988 and 2015 (Figure S2). HURDAT2 is a post-storm assessment conducted by the U.S. National Hurricane Center (NHC) and incorporates data from a variety of sources, including satellite data and, when available, aircraft reconnaissance data (Landsea and Franklin 2013, Jarvinen and Caso 1978). These data typically give measurements of the tropical cyclone center’s 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 tropical cyclones have an additional observation at the time of landfall (Landsea and Franklin 2013).

*Distance-based exposure metric*

For the rain-based exposure metric, cumulative rainfall was estimated for the period from two days before to one day after the date of a tropical cyclone’s closest approach to a county. Daily county-level rainfall was determined by aggregating hourly, 1/8 degree gridded reanalysis data from the North American Land Data Assimilation System Phase 2 (NLDAS-2) precipitation data files (Rui and Mocko 2014). The NLDAS-2 data integrate satellite-based and land-based monitoring, applying a land-surface model to create a reanalysis dataset that is spatially and temporally complete across the continental U.S. (Rui and Mocko 2014, Al-Hamdan et al. 2014). To aggregate to county-level, hourly data at each grid point were summed to create a daily rainfall total, and these grid point rainfall totals were then averaged across all grid points within a county’s 1990 U.S. Census boundaries to create a county-level daily total (Al-Hamdan et al. 2014, Centers for Disease Control 2016). This county-level precipitation data are publicly available through the U.S. Centers for Disease Control’s Wide-ranging Online Data for Epidemiological Research (WONDER) database (Centers for Disease Control 2016, Al-Hamdan et al. 2014). The rainfall-based exposure metric was only available for tropical cyclones through 2011, the period for which the county-aggregated reanalysis rainfall data were available (Centers for Disease Control 2016, Al-Hamdan et al. 2014). Validation analysis of this and other hazard-based exposure data is given in the Supplemental Material.

*Wind-based exposure metric*

Ground-based observations of wind speed are problematic during tropical cyclones, as instruments often fail at high wind speed, while reanalysis data, often available at hourly or higher resolution, can be too smooth to capture wind extremes associated with a tropical cyclone. Therefore, to create a dataset of county-level sustained winds during historical tropical cyclones, we modeled maximum sustained wind speeds at each county’s population mean center (United States Census Bureau 2015). HURDAT2 Best Track data were interpolated from 6-hourly reported values to 15-minute increments using natural cubic splines (Anderson et al. 2017b), and then sustained wind speed was modeled for each county center at each 15-minute increment using a double exponential wind speed model (Willoughby et al. 2006) to estimate maximum ground-level sustained wind speed at each county center (Anderson et al. 2017b). Asymmetry in wind speeds around the tropical cyclone center was incorporated into the wind speed model (Phadke et al. 2003; Anderson et al. 2017b). The maximum value of this modeled wind speed was determined for each county as the maximum windspeed across the 15-minute incremented modeled values throughout the tropical cyclone.

*Flood- and tornado-based exposure metrics*

To identify flood- and tornado-based exposures to tropical cyclones in U.S. counties, we used event listings from the National Oceanic and Atmospheric Administration (NOAA)’s Storm Event Database (National Oceanic and Atmospheric Administration’s National Centers for Environmental Information 2017). For each tropical cyclone, we identified all events with event types related to flooding (“Flood", “Flash Flood", “Coastal Flood") and tornadoes (“Tornado") and that occurred in a county within 500 kilometers of the tropical cyclone’s track and within a five-day window centered on the date of the tropical cyclone’s closest approach to the county (Anderson et al. 2017a). “Flood", “Flash Flood" and “Tornado" events in this database were reported by county Federal Information Processing Standard (FIPS) code. “Coastal Flood" events were reported by forecast zone; for these, the event was matched to the appropriate county if possible (Anderson and Chen 2017). While this database has recorded storm data since 1950, its coverage changed substantially in 1996 to cover a wider variety of storm events (National Oceanic and Atmospheric Administration 2017). We therefore only considered these metrics of hurricane exposure for tropical cyclones in 1996 and later.

*Assessing agreement in exposure classification between metrics*

Two of the exposure metrics (flood- and tornado-based) were inherently binary, since these metrics were based on whether an event was listed in the NOAA Storm Events database or not. For the other exposure metrics, each county was classified as exposed to a tropical cyclone based on whether the exposure metric exceeded a certain threshold (Table 1). We assessed county-level tropical cyclone exposure in the eastern U.S. based on each exposure metric for all land-falling or near-land Atlantic basin tropical cyclones. Depending on available exposure data, this assessment included some or all of the period from 1988 to 2015, a period with 136 tropical cyclones that made U.S. landfall or passed within 250 kilometers (155 miles) of at least one U.S. county (Figure S2).

We measured agreement between exposure metrics in the classification of a county as exposed or unexposed to a specific tropical cyclone. For this measurement, we calculated the within-storm Jaccard index (Jaccard 1901, Jaccard 1908) between every pair-wise combination of hazard metrics. The Jaccard index (*JS*) measures similarity between two metrics (*X1,s* and *X2,s*) for tropical cyclone *s* as the proportion of counties in which both of the metrics classify the county as exposed out of all counties classified as exposed by at least one of the metrics:

This metric can range from 0, in the case of no overlap between the counties classified as exposed based on the two metrics, to 1, in the case that the two metrics classify exactly the same counties as exposed to the tropical cyclone.

**Results**

*Patterns in tropical cyclone exposures in eastern U.S. counties*

We first calculated summary statistics for the exposure assessments (Table 2). There was wide variation in the average number of county exposures per year under the five different tropical cyclone metrics considered. For the tornado metric, there were approximately 50 county exposures identified per year, on average, within our study. For flood and wind metrics, there were substantially more county exposures identified (over 200 per year on average), and even more when assessing exposure using the distance and rain metrics (over 400 per year on average).

We also measured the average number of county exposures per tropical cyclone, within those tropical cyclones in which at least one county was exposed to the hazard (Table 2). The typical number of county exposures per tropical cyclone was lowest when assessing exposure using the tornado metric (median: 7 county exposures per tropical cyclone), higher under the flood and wind metrics (median: 26 and 34, respectively), and even higher for the metrics of rain (median: 68) and distance (median: 84). For every metric except the tornado-based metric, we identified at least one tropical cyclone with over 300 counties exposed. However, the largest-extent tropical cyclone varied by metric (e.g., Beryl in 1994 exposed the most counties based on distance, Frances in 2004 based on rain, and Ike in 2008 based on wind).

*Agreement in county-specific exposure classification to specific tropical cyclones*

The counties that were identified as exposed to a tropical cyclone differed substantially depending on which metric was used in exposure assessment. This was true both when comparing exposure assessment based on distance versus the four hazard-specific metrics considered (wind, rain, floods, and tornadoes) and also when comparing exposure assessments among the four hazard-specific metrics.

Figure 1 gives an example of how sensitive county-level tropical cyclone exposure assessment is to the choice of metric, using as an example Hurricane Ivan (2004), a record-breaking tropical cyclone for its duration as a major hurricane (Franklin et al. 2006). When county-level exposure was determined based on distance, the counties assessed as exposed followed the tropical cyclone’s track, including counties well inland. For the wind metric, only counties near two of the tropical cyclone’s landfalls were assessed as exposed. For rain- and flood-based metrics, however, exposure extended to the left of the track, including counties as far north as New York and Connecticut, while for the tornado metric, exposed counties tended to be to the right of the track and included several counties in central North Carolina, South Carolina, and Georgia that were not identified as exposed to Ivan based on any other metric. Figure S3 provides similar maps for four other example tropical cyclones (selected because they exposed many U.S. counties based on at least one metric), and Figure S4 provides four examples of tropical cyclones in which the disagreement in exposure assessment between rain- and wind-based metrics was particularly notable.

We drew similar conclusions when we investigated all 46 tropical cyclones between 1996 and 2011 (the period for which all five metrics were available) for which 250 or more counties were exposed based on at least one metric (Figure 2). In this figure, each row provides results for a specific tropical cyclone, and each box in that row shows a measure of agreement between a specific pair of metrics in terms of the counties assessed as exposed to that tropical cyclone, with darker colors representing greater agreement in county-level exposure assessments.

For most tropical cyclone, distance-based county-level exposure assessment was at best in moderate agreement with exposure assessments based on the four hazard-based metrics. For almost all tropical cyclones, Jaccard index values between distance and any of the four hazard-based metrics were 0.6 or lower (i.e., out of the counties assessed as exposed to the tropical cyclone by at least one of the two metrics considered, 60% or fewer of the counties had the same exposure assessment under the two metrics). For many tropical cyclones, the Jaccard index values were 0.2 or lower, suggesting very poor agreement in exposure assessment between the metrics. Among the four hazard-based metrics, the tornado-based metric showed universally poor agreement with other metrics in county-level classification across all tropical cyclones considered. For other pairs of metrics, there were also generally large differences in which counties were determined to be exposed to the tropical cyclone, with the Jaccard index values below 0.4 for most metric pairs in most tropical cyclones.

There were, however, a few exceptions—tropical cyclones in which similar counties were determined to be exposed to the tropical cyclone for two or more of the metrics considered. For Floyd in 1999 (Figure S3) and Irene in 2011, for example, county-level classification agreed moderately to well (Jaccard index of approximately 0.5–0.8) for all pairs of exposure metrics except those including the tornado-based metric. These tropical cyclones both made their first U.S. landfall in North Carolina at minor hurricane windspeeds (Category 2 and 1, respectively) and then skimmed the eastern coast of the U.S. north through New England, bringing large rainfall to much of the eastern coast from North Carolina north and causing extensive inland flooding in North Carolina (Floyd) and New England (Irene) (Avila and Stewart 2013, Lawrence et al. 2000). For another set of tropical cyclones (e.g., Lee in 2011 [Figure S3], Ernesto in 2006, and Bertha in 1996), there was moderate to good agreement for all pairwise combinations of distance, rain, and wind, but poor agreement for all other combinations of metrics. Most of these tropical cyclones either skimmed along the eastern coast north of North Carolina (Bertha in 1996, Charley in 2004, Gaston in 2004, Barry in 2007, and Hanna in 2008), in a pattern similar to Hurricanes Floyd in 1999 and Irene in 2011, or made landfall in or near the Florida panhandle and cut across to exit into the Atlantic around North Carolina (Josephine in 1996, Earl in 1998, Alberto in 2006). However, these two sets of tropical cyclones represented the minority of all tropical cyclones considered; for most tropical cyclones, there was low overlap in the counties determined to be exposed to the tropical cyclones between most pairings of metrics.

*Geographic patterns in tropical cyclone exposures*

Strong geographical patterns were clear across tropical cyclone exposure assessments based on these different metrics when the average number of exposures per decade in each county were calculated (Figure 3). Wind-based exposure had a strong coastal pattern, with almost all exposures in counties within about 200 kilometers (124 miles) of the coastline, mostly in eastern North and South Carolina, southern Florida, and the area near the outlet of the Mississippi River. While exposures by rain- and distance-based metrics were also more common in coastal areas compared to inland areas, inland exposures were much more common based on these two metrics compared to the wind-based metric. Rain and, to some extent, flood exposures were characterized by a pattern defined by the Appalachian Mountains, with much lower exposures west of the mountain range than to the east. Almost all tornado-based exposures were in coastal states, with most in Florida, Alabama, South Carolina, and North Carolina and almost none north of Maryland. Flood-based exposures were highest in North Carolina and along the South Carolina coast, as well as further north in New Jersey, southeastern Pennsylvania, and southeastern New York. Notably, some areas of the U.S. that experienced regular exposures to tropical cyclone-related excessive rainfall and floods were not identified as areas of regular risk based on the more commonly used tropical cyclone exposure assessment metrics of wind or distance (Figure 3).

We included a case study in the Supporting Information showing how these differences in exposure assessment across the five metrics considered could strongly influence health-related studies based on physical exposure to tropical cyclones. For this example, we compared estimates of which U.S. counties have the largest expected physical exposure to tropical cyclones among a susceptible subpopulation, Medicare beneficiaries who are reliant on electricity for medical equipment (Supplemental Text, Figure S6) (United States Department of Health and Human Services 2016).

*Software*

To assist with future tropical cyclone impact studies, we created and published open source software that includes the hazard-specific, county-level tropical cyclone data in this paper, as well as tools to explore and map that data (Anderson et al. 2017a, Anderson et al. 2017c). This software includes continuous data for the distance-, rain-, and wind-based metrics, allowing users to also explore different thresholds of these metrics when assessing exposure.

We investigated how well these data correspond with data from other available sources (Figures S7–11). While generally in agreement with data from other sources, there are a few limitations. The wind data are based on modeled, rather than observed, values, and while the modeled wind data generally agree well with post-analysis maximum wind radii from the revised Atlantic hurricane database (HURDAT2; Landsea and Franklin 2013) (Figure S7), for a few tropical cyclones it did not (e.g., Figure S10). The rainfall data are from re-analysis data, which are generally well-correlated with observed ground-based station data but sometimes oversmooth extreme measurements (Figure S8). More details on the assessment of this data are provided in the Supplemental Material.

**Discussion**

Tropical cyclones impact public health in many ways, and epidemiological studies of the health risk and impacts associated with tropical cyclone exposures could help improve preparedness for and response to future tropical cyclones. However, tropical cyclones are multi-hazard events, making it more complicated to measure exposure compared to other weather exposures like temperature and precipitation. Here, we find the county-level tropical cyclone exposure assessments vary substantially when using a distance-based metric versus four hazard-based metrics, as well as among different hazard-based metrics. Our results can inform exposure assessment for future county-level studies of the health risks and impacts associated with tropical cyclones exposures, and the data and software we have created to accompany this article provides multi-hazard, county-level exposure data for multiple tropical cyclone hazards for such studies.

Distance from a tropical cyclone’s track is relatively easy to measure and has been used as an operational metric of exposure to tropical cyclones in previous large-scale studies (examples included in Figure S1). Since distance itself does not constitute a hazard, distance is meant in these cases as a surrogate to capture exposure to hazards from the tropical cyclone. However, here we found that in assessing U.S. county-level exposure to tropical cyclones, distance is, at best, a moderate, and often a very poor, surrogate for exposure to the specific tropical cyclone hazards of high wind, extreme rainfall, flooding, and tornadoes (Figure 2). Therefore, use of distance to assess tropical cyclone exposure for impact studies could result in problematic exposure misclassification, which could mask true associations, even strong associations, between tropical cyclone exposure and outcomes of interest in impact studies (Savitz and Wellenius 2016, Armstrong 1998).

In some cases, this exposure misclassification may be differential (i.e., associated with the outcome of interest or with factors associated with risk of the outcome of interest). For example, tropical cyclone wind exposures tend to be concentrated in counties near the coast, since most tropical cyclones rapidly decrease in sustained windspeed following landfall. However, tropical cyclone exposures based on distance can extend well inland, following the tropical cyclone’s tracks, but may not adequately capture all wind-exposed counties near the coast. In this case, if the etiologically-relevant exposure is high wind but exposure is classified based on distance, the probability of being misclassified as unexposed would be higher in coastal counties, while the probability of being misclassified as exposed would be higher in inland counties. If coastal counties differ from inland counties in either the outcome of interest or in factors associated with risk of that outcome, differential exposure misclassification would exist (Savitz and Wellenius 2016). Such differential exposure misclassification can bias estimates of tropical cyclone effects either towards the null (estimating a lower or null association compared to the true association that exists) or away from the null (estimating a larger association than actually exists) (Savitz and Wellenius 2016, Armstrong 1998). The use of a single hazard-based metric (e.g., wind) could cause similar problems if the impact is driven, at least in part, by a different hazard or by multiple hazards of the tropical cyclone.

Our findings—that county-level tropical cyclone exposure assessment varies substantially when different exposure measurements are considered—aligns with previous research from atmospheric science and related fields on the characteristics of tropical cyclones. While tropical cyclone rainfall and windspeed are often well-correlated when the tropical cyclone is over water (Cerveny and Newman 2000), this relationship often does not remain as strong once the hurricane has made landfall (Jiang et al. 2008). Fast-moving tropical cyclones bring higher risks of dangerous winds inland (Kruk et al. 2010), while slow-moving tropical cyclone are likely to bring more rain (Rappaport 2000) and cause more damage because of sustained hazardous conditions (Rezapour and Baldock 2014). Further, while the likelihood and extent of flooding during a tropical cyclone is related to the tropical cyclone’s rainfall, it is also driven by factors like top soil saturation and the structure of the water basin’s drainage network (Chen et al. 2015, Sturdevant–Rees et al. 2001). However, we did find a small set of tropical cyclone for which for which agreement between metrics were unusually high (e.g., Floyd in 1999, Irene in 2011, Hannah in 2008, Bertha in 1996) For this set of tropical cyclones, the tropical cyclones’ persistent proximity to water may have helped maintain wind speeds in similar patterns to rain and distance exposures, resulting in this moderate to good agreement among exposure assessments based on different metrics.

In our results, wind-based exposure had a strong coastal pattern, with almost all exposures in counties within about 200 kilometers (124 miles) of the coastline. This is consistent with the dramatic decrease in wind intensity that typically characterizes the landfall of tropical cyclones. Exposures by rain- and distance-based metrics often extended further inland compared to the wind-based metric, up to the Appalachian mountains. This agrees with previous research indicating that the Appalachian mountains’ topography both enhances precipitation during tropical cyclones and provides hydrological conditions for severe flooding (Sturdevant–Rees et al. 2001). Almost all tornado-based exposures were in southern coastal states. This pattern echoes previous findings that most noteworthy tropical cyclone-related tornadoes occur on the right side of the tropical cyclone track in Atlantic Basin U.S. storms (Moore and Dixon 2012).

The tropical cyclone exposure averages shown in Figure 3 are limited as estimates of long-term frequencies, as tropical cyclones follow decadal patterns (Kossin and Vimont 2007) likely not adequately captured in the available data. However, these frequency maps, together with evidence from specific tropical cyclones (Figures 1 and 2), do illustrate the potential for strong differences in spatial patterns in tropical cyclone exposures, depending on which tropical cyclone hazards are considered. A few previous studies have sought to determine county-level exposure to tropical cyclones over multi-year periods, including Zandbergen (2009), which estimated exposure in U.S. counties to all U.S. landfalling Atlantic basin tropical cyclones between 1851 and 2003, using both a distance-based metric and a metric that combined distance and windspeed, and Kruk et al. (2010), which explored exposure to hurricane-related winds in the U.S., including inland areas, for 1900–2008. Our results suggest that such exposure assessments may perform well in capturing some tropical cyclone hazards (e.g., wind), but likely miss other potentially dangerous tropical cyclone exposures, especially for hazards that repeatedly threaten northern or inland counties (e.g., rain, flooding).

*Software*

To assist with future tropical cyclone studies, we created and published open source software to accompany this article (Anderson et al. 2017a; Anderson et al. 2017c). Many previous studies have used geographical information system software (e.g., ArcGIS) to assess exposure to tropical cyclones in the U.S. (Grabich et al. 2016, Zandbergen 2009, Czajkowski et al. 2011, Kruk et al. 2010). Here, we offer methods to map and output historic exposure to tropical cyclones that does not require the use of proprietary software but instead uses a package written in the R statistical programming language (R Core Team 2017), which is free and open-source.

In addition to providing tropical cyclone exposure metrics for individual hazards, this software and data also allow users to create tropical cyclone exposure profiles based on multiple hazards or craft exposure indices that combine hazard metrics (Chakraborty et al. 2005, Peduzzi et al. 2009). This ability can be critical, as different hazards of tropical cyclones often act synergistically in causing impacts (Smith and Petley 2009). Further, by including measurements of different hazard exposures in each county for each tropical cyclone, this software allows for the development of more complex exposure indices or models (e.g., random forests, multivariable generalized linear models) that incorporate multiple tropical cyclone hazard measurements.

In creating this hurricane exposure dataset, we aimed for data that are reliable, available for all eastern U.S. counties, and have no missing data within available dates. Further, we have investigated how well these data correspond with data from other available sources (Figures S7–11). However, there are still some important limitations. For example, for a few tropical cyclones, the model-based wind data might differ from post-storm analysis of wind radii (e.g., Figure S10), and the re-analysis rainfall data seems to sometime oversmooth very extreme precipitation (Figure S8). The flood and tornado data came from the National Oceanic and Atmospheric Administration’s (NOAA’s) Storm Events database, which, while a widely-used database of events maintained by NOAA, is based on reports, and so may be prone to underreporting (Ashley and Ashley 2008, Curran et al. 2000), especially in less populated areas (Witt et al. 1998, Ashley 2007), as well as to other reporting errors. While these are important limitations, we selected these data sources as among the best currently available for measuring each of these hazards at a multi-county, multi-year scale.

*Conclusions*

Previous research has highlighted the range of impacts that tropical cyclones can have in U.S. communities. However, studies have varied widely in how they assess exposure to tropical cyclones for exposure, health impact, and other impact studies, in some cases using distance to the tropical cyclone’s track as a surrogate metric of exposure to a tropical cyclone’s hazards. Here we found large differences in which counties are exposed to different hazards of tropical cyclones and that distance is, at best, a moderate, and often a very poor, surrogate for exposure to the specific tropical cyclone hazards of high wind, extreme rainfall, flooding, and tornadoes. Use of distance as a surrogate for any of these hazards could lead to exposure misclassification and, in the case of tropical cyclone risk and impact studies, including epidemiological studies, result in biased estimates. Similarly, if such studies disagree on their findings, it could result from the often poor agreement between exposure classifications based on these different metrics, making studies that use different metrics hard to compare or combine in meta-analyses. Our findings highlight the importance of clarifying the potential pathway from tropical cyclone hazards to health impacts when conducting tropical cyclone epidemiological studies and basing exposure assessment on measurements of these hazards. To help with this, we provide extensive tropical cyclone hazard-related measurements for a large collection of historical Atlantic-basin cyclones, aggregated at the county level to align with the spatial scale at which much health-related data is collected.

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**Table 1.** Exposure metrics considered to assess county-level exposure to tropical cyclones.

|  |  |  |
| --- | --- | --- |
| Metric | Available | Criteria for exposure |
| Distance | 1988–2015 | County population mean center within 100 kilometers of storm track |
| Rain | 1988–2011 | County cumulative rainfall of 75 millimeters or more over the period from two days before to one day after the storm’s closest approach and county population mean center within 500 kilometers of the storm track |
| Wind | 1988–2015 | Modeled maximum sustained wind speed at the county’s population mean center 15 meters per second or higher during the storm |
| Flood | 1996–2015 | Flood event listed in the National Oceanic and Atmospheric Administration (NOAA) Storm Events database for the county with a start date within two days of the storm’s closest approach and county population mean center within 500 kilometers of the storm track |
| Tornado | 1996–2015 | Tornado event listed NOAA Storm Events database for the county with a start date within two days of the storm’s closest approach and county population mean center within 500 kilometers of the storm track |

**Table 2.** Summary statistics for exposure metrics considered to assess county-level exposure to tropical cyclones. A county exposure represents the exposure of a specific eastern U.S. county to a specific tropical cyclone. A county can be exposed to multiple tropical cyclones within a year, and a tropical cyclone can create multiple county exposures under a given metric. The median and interquartile range of county exposures per tropical cyclone is based on the tropical cyclones for which at least one U.S. county was exposed. The years for which data are available for each metric are given in Table 1.

|  |  |  |  |
| --- | --- | --- | --- |
| Metric | Mean (interquartile range) of county exposures per year | Median (interquartile range) of county exposures per tropical cyclone | Tropical cyclone with most counties exposures (# exposed counties) |
| Distance | 433 (224, 503) | 84 (23, 173) | Beryl, 1994 (330) |
| Rain | 401 (152, 553) | 68 (14, 146) | Frances, 2004 (464) |
| Wind | 224 (83, 353) | 34 (8, 80) | Ike, 2008 (355) |
| Flood | 213 (84, 249) | 26 (6, 57) | Ivan, 2004 (317) |
| Tornado | 53 (16, 43) | 7 (2, 16) | Ivan, 2004 (91) |

**Figure captions**

**Figure 1.** Counties classified as exposed to Hurricane Ivan (2004) under each exposure metric (Table 1). The red line shows the track of Hurricane Ivan based on the revised Atlantic hurricane database (HURDAT2 (Landsea and Franklin 2013)). Similar maps for other large-extent storms are given in Fig. S3.

**Figure 2.** Heatmap of Jaccard index values for specific exposure metric pairs within storms. Only storms between 1996 and 2011, and for which at least 250 counties were exposed based on at least one metric, are included. The color of each cell within the main heatmap indicates the value of the Jaccard index (proportion of counties classified as exposed by both metrics out of storms classified as exposed by either metric) for a given pair of metrics for a given storm. Storms are displayed within clusters that have similar patterns in county-level exposure agreement for metric pairs, based on hierarchical clustering using the complete link method Murtagh and Contreras (2012) (i.e., storms in the same cluster tend to have similar patterns for the pairwise strength of agreement among metrics); columns are also ordered based on hierarchical clustering. The colors to the right of the main heatmap for each storm indicate the total number of counties classified as exposed to the storm by any of the five metrics, providing an estimate of storm extent. Maps are available showing the counties identified as exposed under each of five metrics for the widest-extent storm in each cluster: Hurricane Ivan (2004) (Figure 1) and Hurricanes Floyd in 1999, Lee in 2011, Cindy in 2005, and Katrina in 2005 (Figure S3).

**Figure 3.** Average number of storm exposures per decade in U.S. counties for each exposure metric. The criteria behind each of the five metrics is given in Table 1. The years used to estimate these averages are based on years of available exposure data (distance and wind: 1988–2015; rain: 1988–2011; flood and tornado: 1996–2015). Similar patterns persist when analysis is restricted to years with all exposure data available (1996–2011; Fig. S5).