Toward a more effective hurricane hazard communication

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Abstract

Tropical cyclones are among the most devastating natural disasters that pose risk to people and assets all around the globe. The Saffir-Simpson scale is commonly used to inform threatened communities about the severity of hazard, but lacks consideration of other potential drivers of a hazardous situation (e.g. terrestrial and coastal flooding). Here, we propose an alternative approach that accounts for multiple components and their likelihood of coincidence for appropriate characterization of hurricane hazard. We assess the marginal and joint probability of wind-speed and rainfall from landfalling Atlantic tropical cyclones in the United States between 1979 ~ 2017 to characterize the hazard associated with these events. We then integrate the vulnerability of affected communities to have a better depiction of risk that is comparable to the actual cost of these hurricanes. Our results show that the multihazard indexing approach significantly better characterizes the hurricane hazard, and is more appropriate for risk-informed decision-making.

1. Introduction

Tropical cyclones (TCs), known as one of the most catastrophic natural hazards, threaten human lives and cause substantial economic and environmental damages in the United States every year (Pielke and Landsea 1998, Pielke et al 2008, Walsh et al 2016, Klotzbach et al 2018). Due to climate change and increasing sea surface temperature, the frequency and intensity of TCs are expected to increase in the future (Webster et al 2005, Knutson et al 2010). The increasing trend of intensity and destructive potential of TCs highlight the need for understanding and assessing the hazards associated with TCs (Emanuel 2005, Elsner et al 2008).

Landfalling TCs in coastal regions are compound events where damage in the area arises from different hazards. Intensive wind associated with TCs is one of the drivers that causes casualty and property damage, and is likely to increase in certain regions (Elsner et al 2008, Rappaport 2014). Torrential rainfall associated with TCs, although accompanied with weakened wind-speed, has potential impact on risk in coastal communities (Touma et al 2019). Flooding caused by storm surge and concentrated heavy rainfall from TCs also results in loss of life, socioeconomic and environmental damages. Translation speed of the TC is also an important factor such that a slow moving storm in the coastal area not only derives more destructive surge, but also yields in larger cumulative rainfall amounts that pose higher risk to the community (Kossin 2018). TC-driven flood hazards in certain coastal regions are likely to increase in the future due to climate change and sea-level rise (Elsner et al 2008, Woodruff et al 2013, Marsooli et al 2019).

The current scaling system used for characterizing the hazardousness of TCs in the Atlantic, Eastern and Central Pacific (hurricanes) is the Saffir-Simpson scale (SSs) (Simpson 1974). Other regions, such as the Western Pacific, Indian Ocean, and Australia, have different classification for TCs with different terminology (i.e. typhoon, cyclonic storm, and tropical cyclone) and wind-speeds. The SSs is a proxy for TC hazard and categorizes the storm into five categories depending solely on wind-speed. This classification is despite the fact that many processes, such as a well-organized low-pressure core and intense pressure gradient in TCs support uplift, release of latent energy, winds, intense precipitation, and storm surge, which together yield in a multihazard situation. Several studies in the past suggested different methods and approaches to measure the hazardousness of TCs by considering different components such as storm size, surge and waves, rainfall (Senkbeil and Sheridan 2006, Kantha 2006, 2013, Powell and Reinhold 2007, Bouwer 2011, Chavas...
et al 2013, Rezapour and Baldock 2014, Done et al 2018). These studies have focused on quantifying and categorizing the severity of hazards associated with TC events based on physical concepts. Here, we develop a probabilistic approach considering the occurrence of potential hazard and associated vulnerability based on the historical records.

Here we propose a Multihazard Hurricane Index (MHI), an alternative indicator for characterizing TC hazards. For this purpose, we first analyze the data for Atlantic TCs that have made landfall over the continental United States between 1979–2017 and assess the likelihood that extreme wind-speed and precipitation coincide during a TC event. We then integrate the hazard with a socio-economic vulnerability index to make it comparable with the actual damage experienced by affected communities. Comparison between the rank of top seventeen costliest TCs on damage record with the ranking obtained from SSs and MHI helps evaluate the performance of these metrics in providing a comprehensive assessment of hazards and better characterizing and communicating the associated risks.

2. Methods and data

In this study, we propose an alternative approach to estimate the damage relating to TC events considering both wind-speed and precipitation to overcome some of the limitations of the current TC scaling system. We use univariate and bivariate probabilities as the hazard component and a combination of Social Vulnerability Index (SVI) variables as the vulnerability component of the TCs risk. We compare the ranks of the 17 costliest TC events, in the last 20 years, between the National Hurricane Center (NHC) report (National Hurricane Center 2018) and the constructed ranks based on our study.

2.1. Risk, hazard, and vulnerability

Risk is commonly defined as a product of hazard, exposure, and vulnerability (Tessler et al 2015). In this study, we quantify hazard as the marginal/joint probability of exceedance for the variables wind-speed and precipitation relating to a TC event. We also use a combination of SVI variables for the affected region as a proxy for its vulnerability (see section 2.4).

2.2. Precipitation and wind-speed data

Hourly precipitation data is acquired from the phase 2 of the North American Land Data Assimilation System (NLDAS-2) at 1/8 degree spatial resolution. NLDAS precipitation data are generated over the contiguous United States by remote sensing and data assimilation techniques (Xia et al 2012a, 2012b).

HURRicane DATa 2nd generation (HURDAT2), which is known as the best track data for Atlantic TCs, contains information of hurricanes and depression storms from 1851 to 2018 (Landsea and Franklin 2013). The Atlantic TC events with short-duration in the HURDAT dataset are relatively increasing since the late 19th century due to anthropogenic climate change and improvements of the observation techniques (Landsea et al 2010). We use the date, time, latitude, longitude and maximum sustained wind data from 1979 to 2017. Using linear interpolation we construct a new hourly HURDAT2 to make it compatible with the precipitation data from NLDAS-2.

2.3. Sampling pairs of wind-speed and precipitation

We sample 397 pairs of wind-speed and (3-hourly) precipitation observations for these 17 TC events. The precipitation from the NLDAS-2 is extracted using a 5-degree radius buffer area. Then, we generate the buffer area with a 5-degree radius from the center-point of the TC, based on the new constructed hourly HURDAT2. The 3-hourly precipitation record is calculated from those grid cells within the buffer area that includes precipitation data. Multiplying the summation of the existing precipitation depth in each grid cells within the buffer area and the area of the grid cell makes the volume of precipitation. Since the focus of this study is the impact of landfalling TCs, offshore wind-speed and precipitation were not included in the analysis.

2.4. Vulnerability factors

We use the 2016 version of SVI provided at the county scale by Centers for Disease Control and Prevention (CDC) to estimate the vulnerability of the impacted region (CDC 2015). CDC’s SVI has 15 social factors under four different groups: (i) socioeconomic status, (ii) household composition and disability, (iii) minority status and language, and (iv) housing and transportation. We use the three most correlated variables to the damage of the selected events by examining the SVI variables one by one, and those are estimated per capita income, percentage of households with no vehicle available, and percentage of population in institutionalized group quarters. We use a 3 degree radius buffer of which the center point is determined by the front-right intersection of the 2 degree radius of the TC and the coastline to estimate SVI associated with TC events. The shifted buffer is implemented to reflect upon the fact that in the Northern Hemisphere the front right quadrangle of the storm field holds the strongest winds, leading to the most extensive wind damage and highest storm surge. (Ramos Valle et al 2018). We examine different sizes and locations of buffer to obtain the vulnerability component. The 5-degree radius buffer used for the TC related precipitation is covering a large area so that it catches excessive vulnerability information from the TC-impacted area. After the examination,
we find the shifted 3-degree radius buffer have the most correlation to the damage ranks.

2.5. Multihazard Hurricane Index

We employ empirical copulas to model joint behavior of wind-speed and precipitation during TC events. We prefer copulas due to various benefits of these functions versus classic joint probability functions, including their flexibility on marginal and correlation structure selection (Joe 2014). For random variables $X$ and $Y$ (where $n$ is the length of record), based on Sklar’s theorem, there is a corresponding empirical copula defined as (Joe 2014):

$$
Pr \left[ X \leq F^{-1}(u), Y \leq G^{-1}(v) \right] = C(u,v) = \frac{1}{n} \sum_{i=1}^{n} 1 \left( U_i \leq u, V_i \leq v \right)
$$

(1)

Where, $F(X) = Pr[X \leq x]$ and $G(Y) = Pr[Y \leq y]$ are the marginal cumulative distribution functions for variables $X$ and $Y$, $F^{-1}$ is the cadlag inverse of $F$, copula $C$ contains all the information on dependence structure between variables $X$ and $Y$, and $U_i$ and $V_i$ are pseudo copula observations defined as:

$$
U_i = \frac{1}{n} \sum_{j=1}^{n} 1 \left( X_j \leq X_i \right) \quad \text{and} \\
V_i = \frac{1}{n} \sum_{j=1}^{n} 1 \left( Y_j \leq Y_i \right)
$$

(2)

Let variables $X$ and $Y$ be wind speed and precipitation, respectively, driven by a TC, then the non-exceedance probability estimated using equation (1) can be used to calculate the Multihazard Hurricane Index as:

$$
MHI = N^{-1} \left[ 1 - C(u,v) \right]
$$

(3)

Where $N^{-1}$ is the inverse normal function. Such multivariate standardized indexing has previously been used in other fields of natural hazard (Hao and Aghakouchak 2013).

Given the fact that $C(u,1) = u$ and $C(1,v) = v$, $MHI$ is consistent with the SSs at the margin such that $MHI$ values 0.93, 1.48, 1.83 and 2.82 (correspond to non-exceedance probabilities 0.825, 0.930, 0.960 and 0.998) are associated with the wind thresholds for hurricane categories 1 through 4, respectively.
3. Results

Analyzing the wind speed and precipitation data for the 17 costliest Atlantic TCs making landfall in the continental United States from 1979 to 2017 reported by the NHC (figure 1) suggests that wind-based metrics, including the SSs, may result in miscommunication of risk associated with TCs. Among these events, 3 of them are categorized as category 4 hurricanes, 5 of them are categorized as category 3 hurricanes, 8 fall under categories 1 and 2, and one is categorized as a tropical storm based on SSs. In fact, leaving these communities under the impression that a relatively moderate TC is heading the region may not trigger maximal preventive/protective measures in these communities and therefore result in extensive exposure and disastrous situations. For example, Hurricane Katrina (2005), which has been the costliest US TC on record, falls under category 3 however, the wind forcing accompanied with extensive pluvial...
and coastal flooding was not reflected in the SSs indexing. Another example is Sandy (2012), the third costliest US TC classified as category 1 TC and making landfall leading to extensive compound flooding, responsible for most of the damage. Katrina and Sandy are examples of disastrous situations during which combination of multiple hazard drivers result in extraordinary destruction. Each of these drivers may not produce hazardous situation in isolation, thus no univariate metric can appropriately characterize the extent of hazardousness in such cases.

Our analysis suggests that the significant correlation between studied hazard drivers (wind and rainfall) yields considerable difference in categorization of hurricanes. We present a distribution for TCs to provide supporting information how categorization of hurricanes may differ considering the wind-speed and rainfall (figure 2). We use color and symbolic schemes to represent the univariate and bivariate approach, respectively, to effectively illustrate the distribution of the sampled 397 pairs of wind-speed and precipitation as well as the proposing MHI (Please see Method section for details). In fact, an event with wind speed less than 70 mph is not even considered to be a hurricane based on SSs. The same wind hazard when combined with an enormous amount of rainfall (i.e. >$6 \times 10^9$ m$^3$ cumulative precipitation) within the impacted area can be as hazardous as a SSs-based category 3 or 4 hurricane with negligible accompanying precipitation (Please see figure 2). Such compounding effects can be statistically captured using the MHI proposed here.

To evaluate the usefulness of MHI versus SSs, we calculate the hazard level of TCs and then integrate it with a vulnerability index. This is done to compare this proxy of risk with the damage associated with TCs on record (Please see figure 3). We use Spearman’s correlation coefficient to measure the strength of association between ranks in the NHC reported damage (baseline) and estimated risk proxy from SSs.
and MHI. While SSs-based ranked estimates (0.60) show a relatively high association with the baseline, MHI significantly improves upon its performance and show a correlation coefficient of 0.74.

In developing figure 3(a), we use information from the NHC report. In figures 3(b) and (c), we combine the inverse normal of the non-exceedance probability from the univariate distribution (considering only the wind-speed) and the bivariate distribution (considering both wind-speed and precipitation), respectively, with the vulnerability component. Figure 3 shows the superiority of MHI (symbols) versus SSs (colors) by comparing it with the NHC reported damages. Colors are allocated following the SSs (e.g. ranging from yellow (tropical storm) to dark-red (category 4 TC)) and symbols are given based on the MHI (i.e. square is a category 4 TC and x is a tropical storm).

According to figure 3, Katrina, which is a category 3 and a major TC when making landfall, is ranked 1st place in damage in all three cases. Although, there are other events that had higher wind-speeds (category 4 TCs), such as Harvey, Irma, and Charley, Katrina is still ranked 1st in damage. This indicates that the damage is not only associated with wind-speed. Charley, ranked 9th in damage according to the NHC report (figure 3(a)), while it is ranked 5th based on the univariate hazard (figure 3(b)) and 8th based on the bivariate hazard (figure 3(c)). Since Charley is a category 4 and a major TC, it was highly ranked when considering only the wind-speed. However, the damage rank is relatively lower when considering both wind-speed and precipitation. Jeanne shows a similar result as Charley since the rank of damage goes higher when considering only wind-speed while goes relatively lower when considering both wind-speed and precipitation. In contrast, Sandy, a category 1 TC, was ranked 3rd in damage (figure 3(a)) even though it has a low wind-speed. Sandy was ranked 13th in damage based on the univariate hazard (figure 3(b)), which is fairly reasonable when we consider only the wind-speed. This shows the difference between the actual damage and risk estimates based on different TC scaling systems, and also shows how inappropriate characterization of TCs may leave vulnerable communities exposed to these hazardous situations.

4. Discussion and conclusion

Our study reveals that rainfall relating to TCs is an important driver of the TC hazard. The cases of Sandy, Charley, and Jeanne are showing that wind-speed only is not enough to explain the risk of TCs. Also, previous studies show that frequency of intense rainfall relating to TCs will increase in the future and so its inclusion in the TC classification can improve TC hazard estimations (Knutson et al 2010, Rezapour and Baldock 2014). This is inline with the conclusions of literature that suggest methods accounting for multidimensional and adaptive risk estimates are needed for appropriate characterization of TC hazard in the future (Bender et al 2014, Sarhadi et al 2016).

More drivers of TC risk (e.g. storm surge and fluvial flooding), and other characteristics of TC-driven hazards (i.e. duration, direction, and translation speed) may contribute to the total TC hazard. Additional drivers and characteristics, if considered, can help obtain a more comprehensive understanding of TC hazards. This study can be also expanded by adding the exposure/vulnerability components and also advanced techniques for estimation of risk (Dewan 2013). Also, remotely sensed data can be used in both hazard estimation (Tessler et al 2015) and exposure/vulnerability assessment (Wang and Xu 2010, Goldberg et al 2018). Worth noted that, there are uncertainties in the reported TC damage estimates. These damages are often calculated for a certain period after the TC landfall and, given the time it takes for processing the damages and receiving the insurance claims, are subject to some uncertainties (Smith and Katz 2013, Smith and Matthews 2015). Considering these factors help have a better understanding of the TC risk while accounting for uncertainties associated with the damage estimates.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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