Using Synthetic Tropical Cyclones to Characterize Extreme Hurricanes Affecting Charleston, South Carolina

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ABSTRACT

The characteristics and conditions favoring extreme hurricanes remain largely unknown because of their small number in the observational record. Synthetic tracks are capable of providing a large, representative sample of these events, which provides an opportunity to further understanding of extreme characteristics as compared with those of more common tropical cyclones. The authors compare 300 synthetic extreme (100-yr event, $48.9 \text{ m s}^{-1}$) and 300 common (5-yr event, $33.6 \text{ m s}^{-1}$) tropical cyclones for Charleston, South Carolina, for differences in spatial, temporal, and other characteristics. Results suggest that extreme hurricanes have a more-defined spatial and temporal behavior, generally forming off the coast of Africa and making a direct landfall at Charleston. Common tropical cyclones sometimes make prior landfalls, may approach from either the Gulf of Mexico or the Atlantic Ocean, and often decay well before reaching Charleston. They are likely to occur through much of the hurricane season, whereas extreme events are most common during a short period toward the end of August. There is no significant difference between common and extreme translational velocity at landfall. This study demonstrates the opportunity that synthetic tracks provide for understanding the rarest hurricanes and provides initial insight into those affecting Charleston.

1. Introduction

Each year tropical cyclones (TCs) track across the North Atlantic Ocean and Gulf of Mexico, threatening coastal locations across the United States. The track of a particular TC is determined by large-scale steering flows, with a minor contribution from the beta effect. For example, large-scale TC movements may be dictated by the location and strength of the subtropical high [often quantified by the North Atlantic Oscillation (NAO); Elsner et al. 2000]. The NAO, and other teleconnections that affect TC occurrences, such as the Atlantic multidecadal oscillation and El Niño–Southern Oscillation (ENSO), are identified as oscillations, undulating within a prescribed set of values over a given time span.

Tropical cyclone tracks are also subject to daily synoptic weather conditions that may favor a particular direction of movement. Oscillating climatic phenomena such as the NAO create large-scale patterns in the movement of TCs, with smaller inherent fluctuations from synoptic forcing. A broad pattern seen in North Atlantic TC tracks allows them to be categorized as “straight line” or “recurring” tracks (Colbert and Soden 2012), with the NAO being the premier determinant of track type (Elsner et al. 2000) and altering track density along the U.S. coastline on a decadal timeframe (Mei et al. 2014). The location of a TC dictates which climatic variables (e.g., NAO or ENSO) will have a greater impact on its characteristics; therefore, the best understanding of
the hurricane–climate relationship is only possible after distinguishing TCs by track type (Kossin et al. 2010).

A TC’s track is important because it determines its landfall location and, in part, its intensity. The maximum intensity of a TC is mostly a function of its initial intensity, the thermodynamic state of its surrounding atmosphere, and the heat exchanged with the ocean surface (Emanuel 1999), as well as wind shear and low-level vorticity (Mei et al. 2015). In addition, Emanuel (2000), Kossin and Vimont (2007), and Kossin et al. (2010) noted that a TC with longer duration typically reaches greater intensity if it remains over tropical oceans or otherwise relatively warm water. Therefore, an intense TC relative to a particular location will traverse areas of favorable atmospheric and oceanic characteristics for a maximum amount of time before making landfall. Since natural-hazard policy is made on the state or city level (Birkland 1997), it is important for policy makers to understand how track type affects the potential intensity of TCs striking their specific locality.

Our focus is on the track and other distinguishing characteristics of the most intense, rare TCs. Knowledge of such extreme events is important because they often cause the most damage. From 1900 to 2005, major hurricanes (categories 3, 4, or 5 on the Saffir–Simpson scale) accounted for only 24% of hurricane landfalls but 85% of total economic loss from TC events (Pielke et al. 2008). We acknowledge that an extreme event for a less hurricane-prone location may not necessarily be a major hurricane, and therefore, instead of studying TCs of a particular intensity threshold (e.g., category 3), we employ the concept of “relative risk” (Ellis et al. 2015), defining extreme relative to a landfall location.

Our intentions are to develop a robust, basinwide understanding of the connection between the TC intensity and track to further understanding of the spatial patterns and other unique characteristics of extreme TCs. Here we begin with a case study of TCs affecting Charleston, South Carolina, by comparing strong, rare TCs (hereinafter referred to as “extreme” events) and weak, more frequent TCs (hereinafter referred to as “common” events). We gather sets of extreme and common TCs to address the following questions with regard to Charleston:

1) (i) Do extreme events and common events take different tracks to Charleston? (ii) Do extreme events take a more particular track and common events come from a variety of track types?

2) Are there particular TC characteristics that are unique to extreme events?

This research differs from most other track studies in two ways. First, we use a landfall-based approach that views TCs relative to a specific landfall point. A number of papers on hurricane tracks detailed specific track types (e.g., Elsner 2003; Xie et al. 2005; Kossin et al. 2010) but did not focus on where the tracks eventually make landfall [although Kossin et al. (2010) did map landfall locations]. Using a landfall-based approach is helpful for local risk analysis (e.g., Scheitlin et al. 2011) and recognizes that extreme is relative to a specific location, with a definition that varies across the U.S. coast (Jagger and Elsner 2006; Keim et al. 2007; Ellis et al. 2015) and even within a single state (Malmstadt et al. 2010; Trepanier and Scheitlin 2014). Second, we analyze the most destructive TCs. To be specific, we focus on the strongest event expected every 100 years (a 100-yr TC) as compared with the strongest event expected every 5 years (a 5-yr TC). It is often difficult to study such extreme events because of lack of data during the period of record. Our method of overcoming the lack of samples involves using synthetic TC events. Charleston was selected for this case study because the synthetic storm data for this location were readily available from researcher K. Emanuel upon request. The case study provides an opportunity to further investigate the technique of using synthetic tracks for climatological studies, beginning with an East Coast city with moderate risk to TCs from both the Gulf of Mexico and North Atlantic.

The next section describes how the intensity thresholds for extreme and common events are determined for Charleston. It also details the data used in this study. The remainder of the paper uses synthetic extreme and common Charleston TC events to characterize their tracks and other differentiating characteristics. We compare spatial patterns (section 3) of frequency and intensity, temporal characteristics (section 4), and characteristics while impacting Charleston (section 5).

2. Tropical cyclone data

TC data are gathered from the National Hurricane Center Hurricane Database (HURDAT, also referred to as best track). The dataset contains 6-hourly estimations of location and intensity for TCs since 1851 (Jarvinen et al. 1984). Note that the earlier part of the record, specifically prior to the satellite era, is missing TC events and that intensity information is somewhat unreliable prior to 1970. Nevertheless, these data are carefully and consistently used in hurricane climatological studies. To provide greater spatial resolution of observations, the HURDAT TC data are interpolated into hourly estimations using spline interpolations (Jagger and Elsner 2006). The technique for performing spline interpolations of HURDAT using software from...
the R Project for Statistical Computing is outlined in Elsner and Jagger (2013). Hereinafter, any mentions of HURDAT or observed TCs are referring to these hourly interpolated HURDAT events.

a. Quantifying extreme events

This study aims to characterize extreme TC events for Charleston as compared with their more common, weaker counterparts. The “hurricane risk calculator” (HRC; Malmstadt et al. 2010) uses TC data from HURDAT to define common and extreme TC wind risk within a 100-km radius of Charleston. The 100-km radius is the original radius used in the HRC to accommodate the typical city size and ensure that part of the city is affected by the strongest TC winds. The HRC uses HURDAT data within a statistical model that is based on the general Pareto distribution using a peaks-over-threshold method (Malmstadt et al. 2010). Recognizing the small sample size of extreme events in HURDAT, the HRC borrows distribution characteristics across a larger region to estimate local distribution parameters. This technique allows improved estimates of local extreme-wind risk.

The return curve produced by the HRC (Fig. 1) provides an estimate of TC wind risk over time. The red lines indicate the estimated maximum strength of a TC expected once every 5 years (30.6 m s$^{-1}$) and once every 100 years (51.8 m s$^{-1}$) within 100 km of Charleston. The length of the vertical line encompasses the 90% confidence interval about the estimation. For the remainder of this paper we define a common TC event as one that passes within 100 km of Charleston with wind speeds below the upper 90% confidence bound of the 5-yr return level ($\geq 33.6$ m s$^{-1}$) and define an extreme TC event as one that passes within 100 km of Charleston with wind speeds above the lower 90% confidence bound of the 100-yr return level ($\geq 48.9$ m s$^{-1}$).

b. Observed events

Four observed extreme events have passed within 100 km of Charleston during the period 1851–2014. The events are (in order from closest landfall to Charleston): Hurricane Hugo (September 1989), an unnamed October 1893 hurricane, Hurricane Gracie (September 1959), and an unnamed July 1916 hurricane. The tracks for these TCs are shown in Fig. 2b. All four storms travel through the Atlantic Ocean and make a direct Charleston landfall, with the farthest from Charleston being the 1916 hurricane, which passed 70 km away from the center of the city. Three of the storms made landfall northeast of the city center, and Gracie made landfall to the southwest. It can be assumed that the effects of the three storms passing to the northeast could have been even worse given a slightly different track.

c. Synthetic events

There are too few observed samples to analyze the rare, extreme events, and therefore additional data are acquired in the form of synthetic TC events. A variety of North Atlantic synthetic TC models have been used in hurricane research (Vickery et al. 2000; Emanuel et al. 2006; Hall and Jewson 2007; Rumpf et al. 2009; Kriesche et al. 2014). The synthetic tracks used here have also been employed in previous studies, including a quantification of the effects of climate change on TC damage (Hallegatte 2007) and an assessment of the risk of hurricane storm surge for New York City (Lin et al. 2010). The creation of synthetic TCs is described in depth in Emanuel et al. (2008). Instead of modeling events on the basis of the statistics of observed events like in many past studies, these synthetic events are based on the physical mechanisms that control TC characteristics. This approach is especially useful for modeling extreme events that may not have occurred yet in the HURDAT
record but are indeed physically possible. Storm genesis is based on a random seeding method (Emanuel et al. 2008). Once genesis locations are created, the TC is subject to a beta and advection model, which determines where it tracks, and to an intensity model, which characterizes TC intensity on the basis of environmental conditions. Large-scale winds and thermodynamic conditions used to generate the synthetic tracks were provided by NCEP–NCAR reanalyses. The points along the track are given every 2 h. The synthetic tracks used here are spline interpolated to provide hourly information, in the same way that the HURDAT TCs were treated above. The remainder of this paper uses 600 synthetic tracks—300 generated at the common intensity and 300 for extreme storms (K. Emanuel 2012, unpublished data)—to further analyze this relationship between track type and landfall intensity, as well as analyzing additional TC characteristics.

3. Spatial patterns

The tracks of the 300 common synthetic events and 300 extreme synthetic events are shown in Figs. 2c and 2d. With a larger sample size comes a greater assortment of track possibilities than are shown in the observed events (Figs. 2a,b). The common synthetic tracks take a wide variety of approaches to Charleston, similar to the observed tracks, but there is an increased likelihood of a common synthetic event coming from the Atlantic Ocean when compared with those in the historical record. The extreme synthetic tracks primarily make a direct landfall from the Atlantic, but they also exhibit a possibility that was not present in the observed tracks—that a TC may make landfall in the Gulf of Mexico and make it to Charleston at the intensity level of an extreme event.

Pattern interpretation in the tracks is challenging when based on Figs. 2c and 2d alone; therefore, it is
helpful to visualize the tracks in another manner. We employ a framework for visualizing spatial hurricane patterns using a hexagon tessellation. The technique, detailed in Elsner et al. (2012) [and used by Hodges and Elsner (2012), Strazzo et al. (2013), Trepanier et al. (2015), and others], begins by creating a hexagonal tessellation of the study area and overlaying spatial data onto the hexagon grid. The data are summarized within each hexagon. This is especially useful to associate point hurricane characteristics (including frequency and intensity) with raster data layers such as sea surface temperature [as seen in Elsner and Jagger (2013)]. We use the hexagon-tessellation technique to visualize spatial patterns in the synthetic-track sets. Figure 3 displays the spatial frequency of synthetic TC events by denoting the number of TCs that intersect each hexagon. The hexagons further illustrate the differences in patterns for extreme and common tracks. The common tracks (Fig. 3a) are more frequent in hexagons adjacent to Charleston in the Atlantic Ocean, but hexagons west of Florida also have high TC counts (up to 150 observations per hexagon). Extreme tracks (Fig. 3b) have no hexagons west of Florida with greater than 50 TCs, showing the favored approach is from the Atlantic. The extreme TCs have 13 hexagons with at least 100 TC interceptions, greater than the 8 hexagons with at least 100 common TC interceptions. This observation suggests that extreme tracks have a more similar approach than do the common tracks that frequent a wider swath of regularly visited hexagons. In addition, extreme events have more hexagons with at least 50 events farther east, suggesting that more of the extreme events experience similar cyclogenesis locations, presumably in most cases associated with African easterly waves.

It is also helpful to visualize intensity across space. We do this in two ways. First, we plot the average intensity of the common (Fig. 4a) and extreme (Fig. 4b) synthetic TCs when passing through each hexagon. An obvious feature in Fig. 4 is the higher intensities experienced by extreme events, which is due to the selection process of the TCs. More informative are the patterns of intensities, including the location where the TCs are relatively strongest. Second, we plot where each common (Fig. 5a) and extreme (Fig. 5b) event reached its lifetime maximum intensity (LMI). The average LMI for common events was 38.5 m s\(^{-1}\), whereas the average LMI for extreme events was 68.6 m s\(^{-1}\). Figure 5 clearly indicates that common events are more likely to decay far before reaching Charleston, either at a first landfall along the Gulf or elsewhere, or at another location in the Gulf or Atlantic. Meanwhile, extreme TCs are more likely to decay closer to Charleston. Most extreme TCs begin to decay while south of Charleston, prior to making landfall, off the east coast of Florida. This decay pattern has not been the subject of prior research and should be analyzed in observed U.S. Atlantic coast hurricanes.

4. Temporal distribution of TC events
The North Atlantic hurricane season spans 1 June–30 November. Most activity occurs between August and October, with a seasonal maximum in September (Elsner and Kara 1999). Intense hurricanes are known to have a more peaked annual cycle than weaker tropical
cyclones do, with 95% of them occurring between August and October (Landsea 1993).

Next, we analyze the temporal frequency for the synthetic events. The relative frequency of common (Fig. 6a) and extreme (Fig. 6b) synthetic TC activity for each day within the hurricane season (the number of TCs on that calendar day divided by the total number of TCs) is shown in Fig. 6. The actual daily frequencies are shown as points, along with a modeled interpretation that is shown as a curve. Daily TC frequency is modeled with a Poisson regression model and the “gamlss” software package in R (Rigby and Stasinopoulos 2005), as described in Elsner and Jagger (2013). The model uses a penalized B spline (Eilers and Marx 1996), which has a polynomial curve as the limits and maintains the mean and variance of the raw data (Elsner and Jagger 2013). The model provides a smoothed probabilistic representation of the data. It is important to note that these frequencies are based on the 300 synthetic events for each intensity threshold. There are no years associated with these synthetic events, and instead the frequencies here assume that the return levels of the events are the same, making time of year the only differing variable. Therefore, the annual pattern of TC occurrence is shown in Fig. 6 but not an actual estimate of the number of events that would occur in a given year. A slightly larger area under the curve in Fig. 6b is due to the longer life span of extreme events and therefore the larger number of days on which they exist relative to the pattern for common events.
The seasonal peak for Charleston TC activity, including common and extreme events, is in late August (Fig. 6), which is earlier than the North Atlantic basin-wide average (Elsner and Kara 1999). The results differ from prior research that showed that intense hurricanes along the East Coast of the U.S. peak in mid- to late September and are more prevalent in October (20.6% of major East Coast events from 1889 to 1991) than in August (11.8% from 1889 to 1991) (Landsea 1993). One reason for the difference found here could be that Charleston is different from other areas along the East Coast in that it is affected by TCs that enter the Gulf of Mexico as well as recurving TCs along the Atlantic coast. Intense Gulf hurricanes are much more likely in August (31.4%) than in October (2.9%) (Landsea 1993), and, although it has never happened in the observed record, the synthetic events have some of these intense Gulf hurricanes that maintain major-hurricane status until they reach Charleston. As in previous work by Landsea (1993), the extreme events (Fig. 6b) have a sharper seasonal peak than the common events (Fig. 6a). Whereas the common events are capable of capitalizing on a marginal environment, the extreme events rely on the ultimate combination of favorable conditions that are available for a shorter time period.

5. Characteristics during Charleston impact

The generation process for synthetic TCs provided 300 extreme and 300 common Charleston TCs, with the only distinguishing characteristic being the intensity of the TC while within a 100-km radius of Charleston. In this section, we analyze other TC characteristics during the part of their track within this 100-km radius. The R code used to segment the tracks and perform the analyses shown here can be found in Elsner and Jagger (2013).

Section 3 suggests that there are differences in the tracks of the extreme and common TCs, with extreme events being much more likely to make a direct
landfall from the Atlantic and common events being more spread out but more likely to approach after making a previous landfall elsewhere. Therefore, it is likely that common and extreme events strike Charleston while traveling from/in different directions. The direction of TC movement is displayed in a wind rose (Fig. 7) using the “oce” R software package (Kelley 2012). The black wind bars indicate the direction from which the TC is coming, with the size of the bar representing the proportion of TCs that come from that direction. The majority of extreme events come from the southeast and travel to the northwest. The direction of common events is more spread among any southerly direction, with a preference to arrive from the southeast over arrival from the southwest. The most common arrival direction for both event types is 150°–165°. The extreme events had 1620 hourly observations traveling from that direction, while the common events had 904.

Another characteristic that may differ between extreme and common TCs is translational velocity, or the forward speed of the storm. Mei et al. (2012) found that translational velocity increases with TC intensity, especially for the most intense TCs. Translational speeds for common and extreme events while within 100 km of Charleston were analyzed. There is no significant difference in translational velocity between the two sets of storms, but the weaker events have larger variability in forward speed and are more likely to travel at the highest speeds. Translational speed may play a more important role during other parts of the TC’s life cycle; Lin et al. (2009) noted that a certain speed must be reached for a TC in the western North Pacific Ocean to reach a category-5 status.

6. Conclusions

The most extreme hurricanes cause a disproportionate amount of damage to vulnerable coastal cities (Pielke et al. 2008), a fact that produces an immediate need to understand their behavior. Each city has its own level of TC risk, and an extreme event for one city may not be considered to be extreme for another (Ellis et al. 2015). For this study we focus on TCs affecting Charleston and define extreme as a 100-yr event, which, for Charleston, is approximately a category-3 hurricane. Because there are only a few samples of these extreme events in the hurricane database, synthetic tracks (Emanuel et al. 2008) are used to create a set of 300 extreme Charleston events, as well as 300 events at the 5-yr return level that we refer to as common events. We compare the characteristics of the extreme and common TC sets across space and time to determine whether they take different tracks to Charleston and whether they have other distinct characteristics.

The TC tracks and a spatial lattice of their frequencies show that extreme events are more likely to form off the coast of Africa and travel across the North Atlantic, making a direct landfall in Charleston. Common events may approach Charleston from either the Gulf of Mexico or the Atlantic and often make initial landfall elsewhere. Thus, common events usually reach their maximum intensity elsewhere, whereas extreme events for Charleston usually make landfall at their maximum intensity or just after reaching their maximum intensity off the coast of Florida. In addition to their more specific spatial route, the annual timing of extreme TCs is also more confined to the peak of hurricane season. The likelihood of common events is spread throughout much
of the hurricane season, whereas extreme events have a
defined peak of activity in mid-August. There is no sig-
nificant difference between the translational velocities
of the two event types during landfall.

The exact characteristics of extreme TCs remain elu-
sive, because the small sample size provides little sup-
port for statistical analysis. What is known of extreme
hurricanes, along with the results of this paper, suggests
their existence relies on optimum conditions, causing
clusters of them across space and time during the most
favorable environment (Ellis et al. 2015). Predicting
extreme TCs would rely on further understanding the
climatological conditions that favor these events.
Landsea (1993) noted that the interannual and inter-
decadal variability of intense hurricanes is strongly re-
lated to Sahel rainfall variability and concluded that
further research is needed on the variations in the role
that variability in the general circulation plays on the
temporal variability of intense hurricanes. More re-
search (and a continually increasing sample size) will
assist in understanding this relationship, but knowledge
at the local scale will remain scarce for a long time.
Synthetic tracks offer an opportunity to analyze the
most extreme TCs in an attempt to better understand
these catastrophic events. Understanding the effects of
these events could be obtained through similar analyses
of information on storm surge or economic loss.

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