Tropical cyclone storm surge probabilities for the east coast of the United States: A cyclone-based perspective

Katherine L. Towey[1], James F. Booth[1,2], Alejandra Rodriguez Enriquez[3], Thomas Wahl[3]

[1]Earth and Environmental Science, The Graduate Center, City University of New York, New York, NY, 10016, USA
[2]Earth and Atmospheric Science, The City College of New York, City University of New York, New York, NY, 10031, USA
[3]Civil, Environmental, and Construction Engineering and National Center for Integrated Coastal Research, University of Central Florida, Orlando, FL, 32816, USA

Correspondence to: Katherine L. Towey (ktowey@gradcenter.cuny.edu)

Abstract. To improve our understanding of the influence of tropical cyclones (TCs) on coastal flooding, the relationships between storm surge and TC characteristics are analyzed for ~~the east coast of the United States.~~12 sites along the east coast of the United States. This analysis offers a unique perspective by first examining the relationship between the characteristics of TCs and their resulting storm surge and then determining the probabilities of storm surge associated with TCs based on exceeding certain TC characteristic thresholds. Using observational data, the statistical dependencies of storm surge on TCs are examined for these characteristics: ~~distance from~~ TC ~~center, TC~~proximity, intensity, ~~track~~ path angle, and propagation speed~~. Statistically significant but weak~~ , by applying both exponential and linear ~~correlations are found for nearly all sites.~~fits to the data. At each ~~location~~tide gauge along the east coast of the United States, storm surge is influenced differently by these TC characteristics, with some locations more strongly influenced by TC intensity and others by ~~the distance from the TC center~~TC proximity. The correlation for individual and combined TC characteristics increases when conditional sorting is applied to isolate strong TCs close to a location~~, though the fraction of surge variance explained is never greater than 60 %.~~. The probabilities of TCs generating surge exceeding specific return levels (RLs) are then analyzed for TCs ~~that pass~~passing within 500 km of a ~~location~~tide gauge, where between ~~7~~6 % and ~~26~~ 28 % of TCs were found to cause surge exceeding the ~~0.5~~1-yr RL. If only the closest and strongest TCs are considered, the percentage of TCs that generate surge exceeding the ~~0.5~~1-yr RL is between 30 % and ~~50~~70 % at sites north of Sewell's Point, VA, and over ~~70~~65 % at almost all sites south of Charleston, SC. ~~Overall, this analysis demonstrates that no single TC characteristic dictates how much~~When examining storm surge ~~will be generated and offers a unique perspective on surge probabilities that is based on all~~produced by TCs ~~rather than~~, single variable regression provides a good fit, while multi-variable regression improves the fit, particularly when focusing ~~only on those that cause extreme~~on TC proximity and intensity, which are, probabilistically, the two most influential TC characteristics on storm surge.

1 Introduction

~~Regions such as the east coast of the United States (US) have become more vulnerable~~Population increases and development without adequate planning for hazards in coastal regions has led to an increase in exposure and vulnerability to coastal flooding ~~due to the expansion of densely populated communities~~ in low-lying areas (e.g., Strauss et al., 2012; Hallegatte et al., 2013). ~~In these same regions, conditions~~ Some of the factors that ~~generate~~affect storm surges, which drive the largest coastal flooding events, are likely to become worse in the future~~. This can be attributed to~~, through rising sea levels (e.g., Tebaldi et al., 2012; Sweet and Park, 2014; Moftakhari et al., 2015~~),~~) ~~geomorphic changes in the coastal regions (e.g., Familkhalili et al., 2020),~~ and increasing storm intensities with anthropogenic climate change (e.g., Sobel et al., 2016). The ~~magnitude of the~~ changes to these factors will influence how much destruction storm surge may cause in low-lying communities in the future (e.g., Rahmstorf, 2017~~). However, the response of storm~~), and therefore we must fully understand the relationship between surge ~~to changes in the atmosphere and coastal ocean might not be monotonic. Thus, we need to expand on our~~ and these factors in the current ~~understanding of~~climate. The study herein will thus focus on the relationship between TC characteristics and storm surge ~~behavior, in terms~~for the east coast of the ~~drivers of its variability.~~United States (US).

~~For~~Along the US east coast, both tropical cyclones (TCs) and extratropical cyclones (ETCs) can create storm ~~surge~~surges that generate major hazards to coastal areas (e.g., Zhang et al., 2000; Colle et al., 2010; Booth et al., 2016). For ETCs, different atmospheric circulation ~~scenarios~~patterns can produce large surge, with the highest median surge occurring with a slow-moving ETC in conjunction with an anticyclone located to its north (Catalano and Broccoli, 2018~~), and the~~). The most-common track paths of ETCs causing storm surge differ for the Mid-Atlantic and the Northeast US (Booth et al., 2016). Additionally, cities that are farther north tend to have less TC-related storm surge extremes (Needham et al., 2015). This is because at higher latitudes, TCs encounter environmental conditions that do not promote the sustainability of TCs, including cooler sea surface temperatures and increased wind shear associated with the jet stream, particularly later in the Atlantic hurricane season. However, even as far north as Boston, MA, four of the top 10 surge events since 1979 were caused by TCs (Booth et al. 2016). ~~We know~~

Although both TCs and ETCs can generate surge, it is important to note that some of the ~~atmospheric dynamics of TCs and ETCs~~energetics of the atmosphere differ for TCs and ETCs. While both TCs and ETCs are fundamentally low-pressure systems, TCs derive their energy through latent heat release over warm ocean waters, whereas ETCs gain their energy from the presence of air masses with different temperature and moisture characteristics (e.g., Jones et al., 2003; Yanase and Niino, 2015). ~~Because of~~Due to these differences in storm dynamics, flood exceedance curves for TCs and ETCs can ~~have~~exhibit different characteristics when ~~one considers~~considering long timescales (i.e~~.g~~., 100-~~year~~yr events~~; ~~) as more extreme events are likely to be associated with TCs (Orton et al., 2016). Thus, even though TCs occur much less frequently than ETCs along the US east coast~~,~~, (e.g., Booth et al., 2016), individual TCs can cause more damage~~.~~ as they often are associated with more moisture and stronger winds than ETCs. Therefore, it is ~~important~~the focus of this research to understand how differences in ~~TC~~certain characteristics of TCs relate to storm surge.

Several studies have utilized numerical models to assess the relationship between storm surge and TC characteristics. ~~Lin et al. (2010) showed an exponential relationship between increasing wind speed and increasing surge at New York City. The result was based on thousands of synthetic storms for a specific track path, and the relationship was still quite noisy (Fig. 5 in Lin et al., 2010). Garner et al. (2017) illustrated the uncertainty associated with shifts in TC tracks near the Battery in New York City.~~Synthetic TC tracks along the Mid-Atlantic and the Northeast US have been heavily utilized to identify various relationships between surge and wind speed (Lin et al., 2010), TC tracks (Garner et al., 2017), and landfall angle (Ramos-Valle et al., 2020). Additionally, Camelo et al. (2020) simulated 21 storms in the Gulf of Mexico and along the east coast of the US and found no individual TC characteristic correlates well with storm surge. ~~In the Gulf of Mexico, Irish et al. (2008) found a noisy, but statistically significant relationship between storm surge amplitude and the size of TCs.~~The effect of the size of hurricanes on storm surge was found to be significant in the Gulf of Mexico (e.g., Irish et al., 2008; Needham and Keim, 2014). While comparing both observed and modeled surge heights, Bloemendaal et al. (2019) affirmed that surge height is influenced by the intensity and size of TCs in addition to coastal complexities and slope. Peng et al. (2006) examined the sensitivity of surge induced by both offshore and onshore winds to wind speed and direction. Needham and Keim (2014) empirically found that storm surge correlates better with TC winds pre-landfall as opposed to winds at landfall; Roberts et al. (2015) found a similar result for all storm types. ~~Modelling~~Modeling work also suggests that with anthropogenic climate change, TCs will become stronger~~,~~ and peak intensity will occur at higher latitudes, and thus, changes to the intensity, frequency, and tracks of TCs are ~~predicted~~likely to impact storm surge (Knutson et al., 2020). While many studies have focused on utilizing synthetic tracks and models to better understand the relationship between storm surge and TCs, to our knowledge, no previous assessment has examined historical surge observations ~~outside of a regional area,~~ with a focus on surge variability relative to TC characteristics in addition to calculating storm surge exceedance probabilities based on TC characteristics. Therefore, we have designed an analysis to utilize past observations to determine the correlation between ~~TC characteristics and storm surge~~storm surge and TC characteristics as well as utilize those characteristics to determine the likelihood of surge exceeding some threshold at various locations along the eastern US.

~~We note that~~The magnitude of storm surge ~~magnitude~~ at a location is also impacted by coastal characteristics ~~over a particular location~~, such as its bathymetry (Weaver and Slinn, 2010~~)~~), wind drag coefficients and bottom friction (Akbar et al., 2017), coastal complexities (Bloemendaal et al., 2019), depth of near-shore waters combined with the astronomical tide cycle (Rego and Li, 2010; Talke et al., 2014), and geomorphic changes in the coastal regions (e.g., Familkhalili et al., ~~). However~~2020). While these factors are important to surge, our focus ~~herein~~ will be ~~TC~~on characteristics~~.~~ related to TCs, including the TC proximity to a tide gauge, TC ~~information, such as the track~~ intensity, measured through its mean sea-level pressure (MSLP), TC path~~, storm strength~~ angle, and ~~track direction,~~TC propagation speed, all of which can be ascertained from historical cyclone track information. ~~These TC characteristics~~Since this TC information as well as storm surge data are timestamped, we can ~~then be related to storm surge itself~~relate the two datasets together. By utilizing this method of storm attribution, the analysis herein examines surge events and TCs in the observed record to understand empirically how TC characteristics can influence storm surge.

In this paper, we present a two-part analysis that examines how the magnitude ~~and frequency~~ of storm surge events associated with TCs ~~vary~~varies based on the characteristics of the TCs themselves at various locations along the east coast of the US. Section 2 describes the data and methods used in calculating storm surge and associating storm surge events with TCs. Section 3 is divided into two parts, with part one first analyzing how TC characteristics both individually and in conjunction with one another correlate with the magnitude of storm surge. We further explore if examining TC characteristics individually or combined with one another improves the predictability of storm surge. Part two computes the return levels of storm surge and examines the likelihood of the return level of storm surge being exceeded by TCs that meet certain criteria~~ at various locations along the east coast of the US~~. The paper concludes with a discussion of the results in section 4.

2 Data and Methodology

Section 2.1 describes how the storm surge data is calculated from the original water level data. Section 2.2 details ~~how~~the algorithm which associates storm surge events ~~are associated~~ with TCs as well as the TC characteristics that are examined in ~~determining the relationship between~~relation to the storm surge~~ and TC characteristics~~.

2.1 Storm Surge Data

The water level data utilized in this analysis is obtained from the National Oceanic and Atmospheric Administration (NOAA) Tides and Currents website (NOAA, 2021). Twelve tide gauges, which record the water levels, that span along the east coast of the US were selected for this analysis (Table 1). Our analysis begins in 1946 for most sites, unless the station has data available beginning in a year later than 1946, as shown in Table 1~~.~~, and ends in 2019 for all sites. It is important to note that the water level data is not continuous for all locations and thus, some sites may contain gaps in the data. The year 1946 is selected as the starting ~~date~~year in our analysis because in 1945, the NOAA~~-~~-predicted tide and/or sea level data appeared to have a timing issue at some locations where the data ~~are~~were offset, which ~~causes~~caused the difference between the sea level and the tide to have a tidal pattern.

The water level data is initially provided in hourly time intervals. Each water level time series results from a combination of the mean sea level, astronomical tides, and non-tidal residual, which mainly contains the surge component. ~~We are aware that~~While the wave setup ~~can influence~~is an important component to the water level~~, but~~ (e.g., Phan et al., 2013, Marsooli and Lin, 2018), we neglect this component~~.~~ in our calculation of storm surge due to its overall complexities and its variations based on location and storm intensity. Additionally, the wave setup in the non-tidal residual is minimal because tide gauges are typically located in protected areas, such as harbors and bays. To obtain surge ~~levels~~heights, we first remove the astronomical tide, which is provided on the NOAA Tides and Currents website (NOAA, 2021), from the water level data and then remove low-frequency trends by subtracting a 365-day running mean of the water level for each site's water level time series. We refer to the resulting value as surge. Using hourly surge, we find the maximum surge per day and refer to this value as the maximum daily storm surge.

Table 1. Locations of tide gauges used in analysis with their latitude, longitudelocation and length of data record., which spans through 2019 for all sites. TCs are separated based on whether they undergo extratropical transition (ET TCs) or do not (non-ET TCs). The number of TCs within 500 km before and after the removal of missing mean sea-level pressureMSLP values are included here. The average SLPMSLP of TCs through the time--averaging technique within 500 km, 250 km, and 100 km, which are referenced throughout the manuscript, are included here.

Location	Latitude	Longitude	Starting Year of Record Length	Number of non-ET TCs (ET TCs) within 500 km	Number of non-ET TCs (ET TCs) within 500 km with SLPMSLP available	Average SLPMSLP of non-ET TCs within 500 km (hPa)	Average SLPMSLP of non-ET TCs within 250 km (hPa)	Average SLPMSLP of non-ET TCs within 100 km (hPa)
Portland, ME	43.66° N	70.25° W	1945-2019	9634 (62)	8331 (52)	987.2078983.5	989.7761987.8	995.1048981.1
Boston, MA	42.36° N	71.05° W	1945-2019	11850 (68)	10244 (58)	987.9074983.1	990.6463983.3	988.3217985.0
Newport, RI	41.51° N	71.33° W	1946-2019	12658 (68)	10853 (55)	987.4477981.7	990.0447984.0	993.0641988.7
New York, NY	40.7° 70° N	74.02° W	1946-2019	12970 (59)	11564 (51)	988.9265984.8	989.6776984.5	988.5800984.6
Sandy Hook, NJ	40.47° N	74.01° W	1946-2019	13273 (59)	11767 (50)	988.6768984.6	990.5679984.2	989.6271984.6
Cape May, NJ	38.97° N	74.96° W	1966-2019	8549 (36)	8549 (36)	990.5786985.6	990.9775985.2	980.9500977.6
Sewell's Point, VA	36.95° N	76.33° W	1946-2019	161109 (52)	145101 (44)	988.9418987.0	989.2514985.1	994.7525990.9
Duck, NC	36.18° N	75.75° W	1979-2019	8759 (28)	8759 (28)	989.3469986.2	990.2318985.7	991.0889988.1
Charleston, SC	32.78° N	79.92° W	1946-2019	159122 (37)	135104 (31)	988.1105986.6	988.9286987.1	990.5564988.9

Fort Pulaski, GA	32.04° N	80.90° W	1950-2019	137110 (27)	11996 (23)	987.9745986.4	989.80031	992.82120
Fernandina Beach, FL	30.67° N	81.47°W	1946-2019	154128 (26)	133113 (20)	990.0043989.5	989.1333988.7	991.54924
Key West, FL	24.55° N	81.81° W	1950-2019	117113 (4)	104100 (4)	990.29467	985.97174	981.9602982.0

2.2 Methods

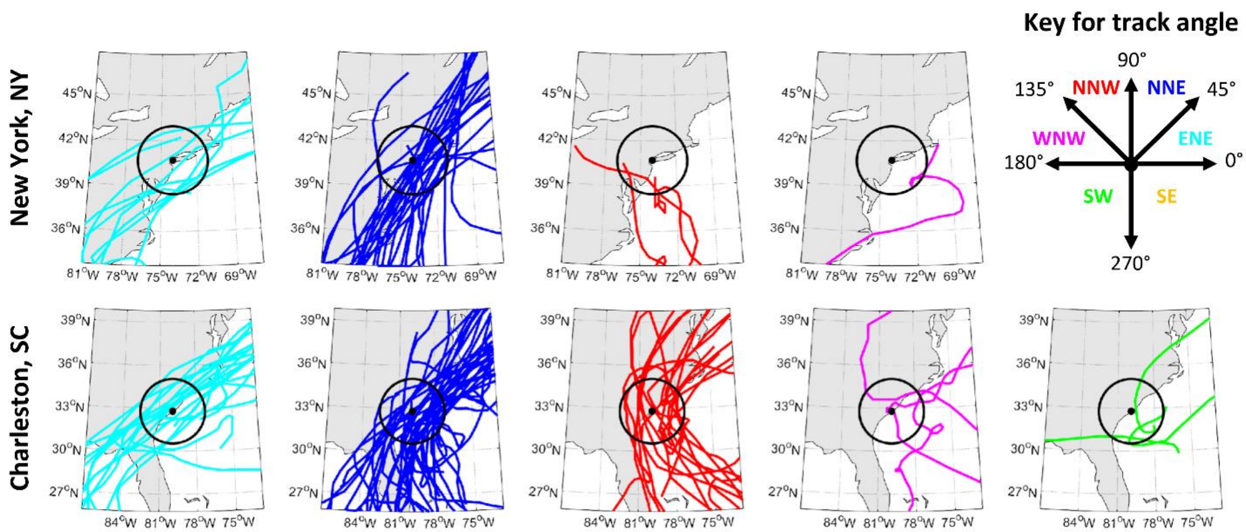
Using our dataset of maximum daily storm surge for each site, we associate the surge events with TCs. The National Hurricane Center's Atlantic hurricane database (HURDAT2; Landsea and Franklin, 2013) is used to identify TCs. The HURDAT2 database provides at least 6-hourly observations of each TC, and in some rare instances, at a shorter time interval of 3 h; therefore, we use only the 6-hourly data for all TCs. The TC variables we utilize are its location, central mean sea-level pressureMSLP minimum (SLP)units: hPa), and maximum sustained surface wind intensity.speed, defined as the maximum 1-min average wind speed at 10 m (units: knots). All TCs that pass within a specified distance centered on each500 km of a tide gauge site are retained for this analysis, with results for multiple distance thresholds reported in Section 3.. We initially consider a search radius of 500 km due to the typical spatial sizes of TCs, but also examine smaller search radii of 250 km and 100 km. Generally, a search radius beyond 500 km is too large when considering the spatial size of TCs (e.g., Booth et al., 2016). Distance from tide gauges to the TC centers to sites are calculated using great circles. We then find all time steps along the TC track when the TC was within the specified distance500 km and examineexamined what the maximum daily storm surge was at each of those time steps. We consider all TCs in the HURDAT2 database that are categorized as a tropical storm, or hurricane, or having undergone extratropical transition during at least one time instance when the storm is within the search distance500 km. Thus, if a cyclone in the database only reaches tropical depression strength during the time that it is within the search distance for a specific site, it is not included in our analysis. Hereafter, we simply refer to these storms that we are analyzing as TCs500 km of a specific site, it is not included in our analysis. Additionally, we exclude any TCs that undergo extratropical transition (ET) and are classified as "extratropical" in HURDAT2 while the TC is within 500 km of a tide gauge since these TCs can no longer be considered purely tropical in nature. The percentage of TCs that undergo ET increases with latitude, with the six most northern sites in this analysis observing over 40 % of TCs that undergo ET (Table 1). Additional analysis for these six sites comparing non-ET TCs and ET TCs is presented in section 3.

The 6-hourly To determine the maximum storm surge associated with a TC at a given location, only the time steps for when the TCs area TC was within a specified distance of a site are associated with 500 km of a tide gauge are considered as when the storm surge could be realistically attributable to a TC. First, the maximum daily storm surge that occurred on the day of each time step is assigned to each time step along the TC track. For example, if there are five time steps spaced apart by 6 h and three of the five time steps are on the same day, those three time steps would be assigned the same storm surge value – the maximum surge for that day. TheThen, the highest maximum daily storm surge that occurred when the TC isof all of these time steps within a specified distance of a site500 km is the one storm surge value that we associate with the TC. Thus, the storm surge value at a given location attributed to a TC as it is the highest maximum daily storm surge value of all values whenproduced by the TC is within a specified distance of a site. We note that the maximum daily storm surge we find in this manner is not necessarily the storm surge that occurs at the time when the TC was closest to site, instead, the maximum surge is the largest surgethe tide gauge. However, if there are multiple time steps while the TC was within 500 km that have the same surge value, the closest time step along the TC track is utilized in the analysis. While it is near physically impossible for two TCs to be within 500 km of each other, the algorithm is set up such that in the case that can be realistically attributable to the TCthere are multiple TCs (or ETCs in future analyses) within 500 km of a tide gauge, the closest one is the one more likely to be attributable to the storm surge and thus is the one that is inretained for the vicinity of the siteanalysis.

The first part of our analysis utilizes variables provided in the HURDAT2 dataset to examine how the maximum daily storm surge varies with distanceTC proximity, intensity, track path angle, and propagation speed. In our analysis of the relationships between storm surge and TC characteristics and storm surge,, we apply both linear regressionand exponential fits. The residual standard error (RSE) is usedcalculated to generate assess both the linear best fits. Correlationand exponential fits of each relationship where a lower RSE indicates a better fit. This method was utilized in Needham and Keim (2014) in examining the relationship between surge and wind speed. When analyzing linear fits, correlation coefficients are calculated using the Pearson method. Single and multiple linear regression analyses are presented to determine the predictability of these TC characteristics on storm surge. To test for statistical significance, we use the p-value method, where we select a significance level of 5 %. The null hypothesis is that the correlation coefficient of our data sample is not significantly different from zero. If the p-value is less than the significance level, of 5 %, we reject the null hypothesis and thus conclude that there is a statistically significant relationship among our data.

For TC intensity, our primary analysis uses SLPMSLP. Since SLPMSLP data is missing for some instances, we use the average of SLPMSLP values that are recorded over the time periodwindow from 18 hoursh prior to the surge maximum to 6 hoursh post surge maximum. This choice of timing is motivated by the results of Needham and Keim (2014) and Roberts et al. (2015). Wewho found storm surge best correlates with TC winds 18 h prior to landfall. Additionally, we tested different time windows, shifting it forward or backward in time relative to the time of the surge maximum, including 24 h prior to 12 h post, 12 h prior to 6 h post, and 6 h prior to 6 h post and found that changes in results were negligible (the correlation between surge and MSLP for each time window does not shown). This time-averaging technique vary significantly. The time window from 18 h prior to 6 h post displayed the highest correlation and was thus chosen as the time window to average TC characteristics over. Hereafter, this will be referenced throughout the analysis and appliedwith respect to other variables. throughout this analysis as the time-averaging technique. If there are no recorded SLPMSLP values during this time-averaging periodwindow, we remove the TC from our analysis. Table 1 indicates the number of TCs within 500 km for each site before and after we remove those TCs from our analysis. We also analyzed the maximum surface wind ~~intensity~~speed as a measure of TC intensity but found that wind speed and ~~SLP~~MSLP are highly correlated (~~not shown~~S1), and thus, we just consider ~~SLP~~MSLP as a measure of TC intensity for this analysis.

For the calculation of ~~track~~TC path angle, we ~~quantify~~calculate the change in latitude and longitude between ~~subsequent~~time steps separated by five time steps along the track of the TC~~ and use~~. This method allows us to examine the ~~vectors averaged over~~ change in the ~~24 h time interval described for our analysis of SLP to get one value~~direction of the ~~track~~TC over a longer period of time as opposed to between consecutive time steps. The atan2d function in MATLAB is then utilized to find the TC path angle~~ representative of that time frame. The track~~, as this function returns the four-quadrant inverse tangent. The TC path angles range from 0° or 360° (eastward) to 90° (northward) to 180° (westward) to 270° (southward). Examples of TC tracks and their respective ~~track~~ path angles for New York, NY and Charleston, SC are shown in ~~Fig.~~figure 1. The TC path angles are not grouped relative to the site of the tide gauge, rather they are relative to the direction the TC is moving around the time of the surge maximum. For both New York and Charleston, the majority of TCs propagate toward the northeast ~~relative to each site~~around the time of the surge maximum, though there are many TCs that also move toward the northwest ~~relative to~~in Charleston.



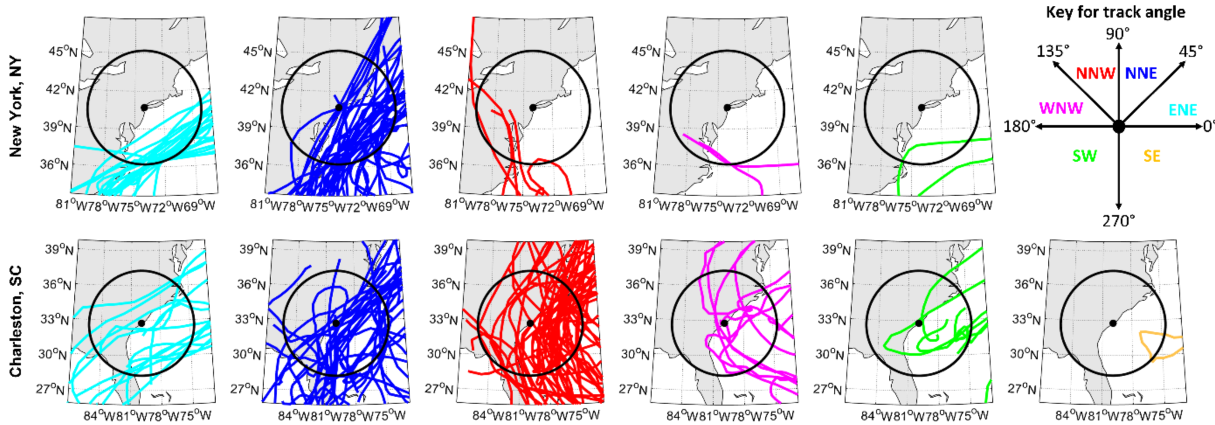


Figure 2. Tracks of TCs within ~~250~~500 km for New York, NY (top row) and Charleston, SC (bottom row) separated by ~~track~~ path ~~angle~~angles around the time of the surge maximum. Colors of tracks indicate the ~~track~~ path angle as portrayed in the key and include toward the ENE (light blue, column 1), NNE (dark blue, column 2), NNW (red, column 3), WNW (magenta, column 4), ~~and~~ SW (green, column 5~~). No tracks moved toward the~~), and SE~~.~~ (orange, column 6). The tide gauge location is indicated by ~~a~~the black dot and the search radius of ~~250~~500 km around the location is indicated by the black circle.

Propagation speed is calculated using the distance traveled per 6-hourly time step based on great circles. We then apply the ~~same~~ time-averaging technique ~~described for SLP to the calculations of propagation speed~~. For the data that we analyzed, however, the relationship between the surge maximum and TC propagation speed is negligible and is not included in this analysis. This does not mean that propagation speed does not have some physical impact on the surge generated by a TC~~; it means~~, but rather that ~~the signal of that forcing~~its sole influence on surge is ~~too small~~more complex compared to the ~~noise associated with all of the~~ other ~~variability in the mechanisms~~variables that influence surge.

The second part of this analysis examines the ~~likelihood of the rate of occurrence~~exceedance probability of a storm surge event through calculating the storm surge ~~levels~~heights for various return periods at each site. Surge return levels are calculated using a peaks-over-threshold method (Coles, 2001) by fitting a Generalized Pareto Distribution (GPD) to the top 1 % of ~~hourly~~daily storm surge events at each location. Before performing the fitting to the GPD, the events over the threshold are de-clustered using a ~~3~~2 d window, so we satisfy the assumption of independence (e.g., Wahl et al., 2017). Return levels at ~~0.5~~ 1-yr, ~~1~~ 2-yr, ~~2 yr,~~ 5-yr, 10-yr, and 25-yr intervals are determined from the GPD and are included in Table 2. ~~Focusing on~~The likelihood that a TC meets certain criteria (i.e., TC proximity of within 500 km of a location) and produces storm surge exceeding the ~~0.5 yr return levels, which provides us~~threshold associated with a ~~large enough sample size, we then do~~1-yr return level is examined through a probabilistic analysis ~~in which we determine how many TCs produce a surge maximum that exceeds the 0.5 yr return level threshold and have TC characteristics that meet certain criteria~~.

Table 2. Return levels (m) for each location for return periods of ~~0.5-yr,~~ 1-yr, 2-yr, 5-yr, 10-yr, and 25-yr intervals.

Location	~~0.5 yr~~	1-yr	2-yr	5-yr	10-yr	25-yr

Portland, ME	0.~~639~~160 m	0.~~742~~971 m	0.~~850~~086 m	0.~~997~~297 m	1.~~112~~913 m	~~1.2718 m~~
Boston, MA	0.~~747~~168 m	0.~~875~~881 m	~~1.0040~~0.98 m	1.~~173~~011 m	1.~~300~~327 m	~~1.4680 m~~
Newport, RI	0.~~614~~760 m	0.~~726~~072 m	0.~~845~~689 m	1.~~017~~204 m	1.~~158~~327 m	~~1.3608 m~~
New York, NY	0.~~795~~081 m	0.~~947~~198 m	1.~~112~~822 m	1.~~354~~841 m	1.~~556~~969 m	~~1.8523 m~~
Sandy Hook, NJ	0.~~803~~483 m ~~0.9607 m~~	1.~~134~~500 m	1.~~392~~426 m	1.~~611~~347 m	1.~~936~~279 m	
Cape May, NJ	0.~~708~~473 m	0.~~825~~785 m	~~0.9450~~1.00 m	1.~~106~~110 m	1.~~230~~522 m	~~1.3985 m~~
~~Sewells~~Sewell's Point, VA	0.~~675~~273 m	0.~~809~~688 m	~~0.9551~~1.07 m	1.~~165~~922 m	1.~~340~~643 m	~~1.5939 m~~
Duck, NC	0.~~610~~761 m	0.~~703~~671 m	0.~~796~~283 m	0.~~917~~992 m	1.~~009~~604 m	~~1.1302 m~~
Charleston, SC	0.~~575~~153 m	0.~~669~~463 m	0.~~773~~180 m	0.~~926~~197 m	1.~~055~~125 m	~~1.2454 m~~
Fort Pulaski, GA	0.~~679~~063 m	0.~~786~~275 m	0.~~902~~092 m	1.~~069~~506 m	1.~~208~~127 m	~~1.4086 m~~
Fernandina Beach, FL	0.~~791~~076 m	0.~~918~~488 m	1.~~049~~106 m	1.~~227~~221 m	1.~~366~~245 m	~~1.5556 m~~
Key West, FL	0.~~222~~320 m	0.~~256~~724 m	0.~~296~~731 m	0.~~359~~539 m	0.~~415~~955 m	~~0.5046 m~~

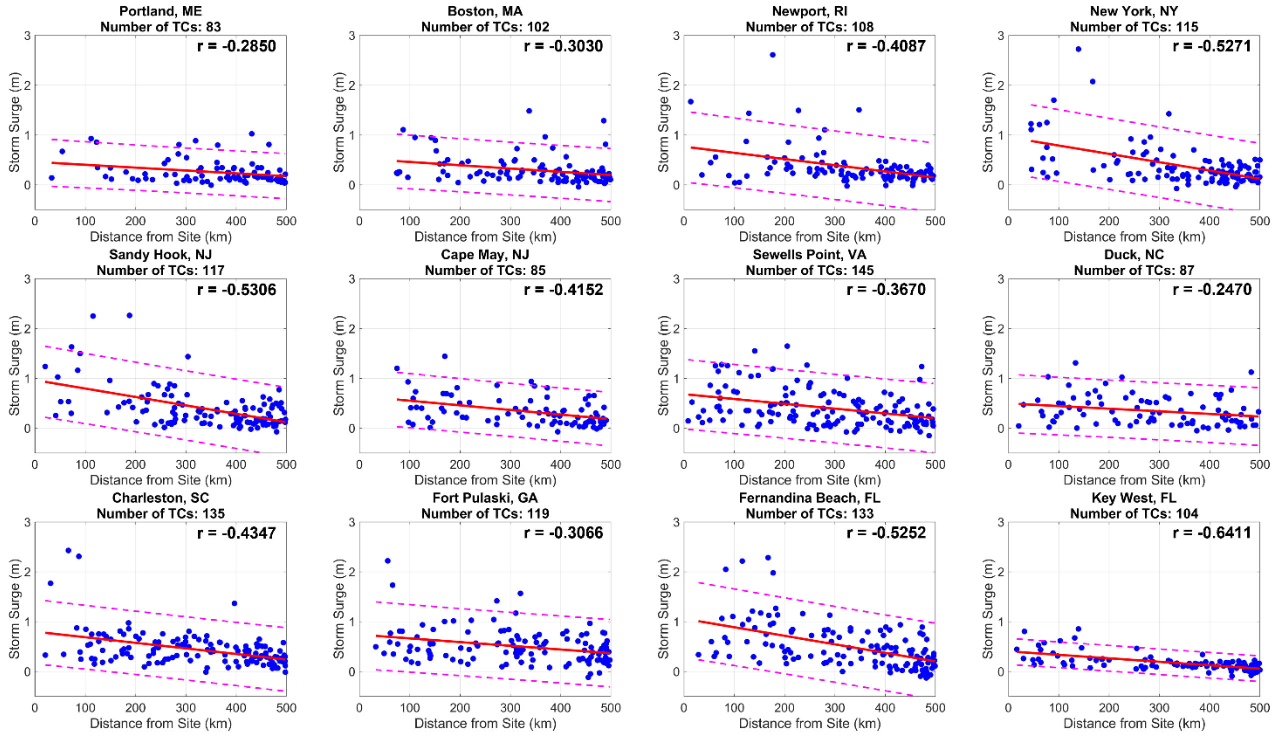
3 Results

Section 3.1 examines the correlation between storm surge and TC characteristics individually, combined, and through ~~conditionally~~conditional sorting. Section 3.2 assesses the probabilities associated with TCs producing storm surge exceeding the ~~0.5~~1-yr return level given certain TC characteristics.

3.1 Storm surge correlation with TC characteristics

For our correlation analysis, the first characteristic we analyze is the distance between the TC center and the tide gauge~~ site~~, hereafter referred to simply as ~~distance~~TC proximity. When considering TCs that pass within 500 km of a location, the magnitude of storm surge generally increases for TCs that are closer to a given site (Fig. 2). ~~Each site exhibits a negative correlation between storm surge and distance and the relationship is statistically significant at all sites based on the method described in Section 2.2. ~~Many of the largest storm surge events do tend to be at distances less than 200 km for most locations. However, as seen in ~~Fig. ~~figure 2, there are also instances where TCs close to a location generate relatively small storm surge. Conversely, there are also instances where TCs are further away from a location, but result in high storm surge (e.g., ~~Boston, MA in Fig. 2). While the correlation is low for most sites, there is a moderate relationship at New York, NY, Sandy Hook, NJ,~~

~~Fernandina Beach, FL, and Key West, FL, suggesting that distance alone is not a strong enough predictor of storm surge.~~Charleston, SC in Fig. 2). For most locations, RSE is very similar when applying both linear and exponential fits, with the greatest difference seen at Newport, RI. When examining storm surge as a function of distance for ET TCs, the fit worsens for the six most northern sites, which have at least 40% of their TCs undergo ET (S2).



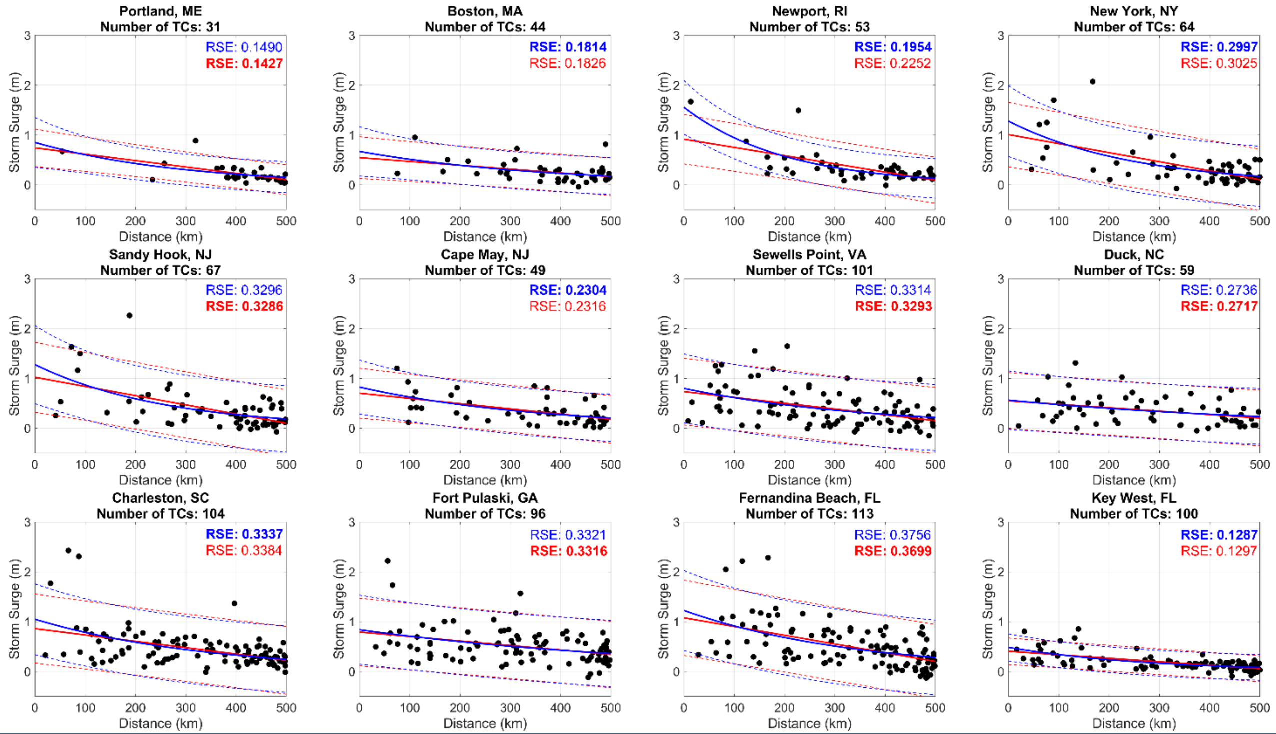
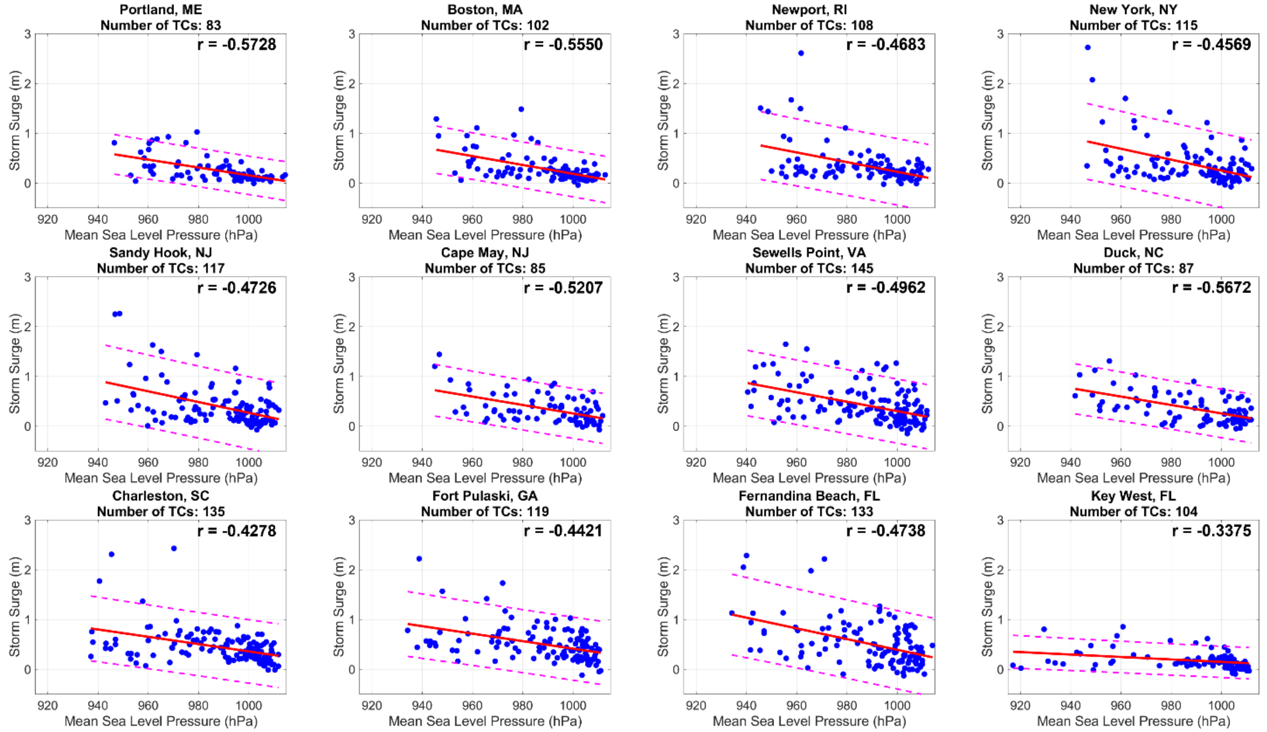


Figure 2. Linear ~~fit~~ (red solid line) and exponential (blue solid line) fit between storm surge (m) and ~~distance of~~ TC ~~from site~~proximity (km) with 95 % confidence intervals (dashed ~~magenta line~~lines) for all TCs within 500 km. ~~Correlation coefficient, r,~~Residual standard error (RSE) is provided ~~at~~for each ~~site and is bold if it is statistically significant.~~type of fit with the lower value bolded.

The second characteristic we consider is TC intensity, based on the ~~SLP~~MSLP of the TC, as discussed in Section 2.2. All locations display a similar relationship in which the magnitude of storm surge is larger for TCs with lower ~~SLP~~MSLP, which generally signifies a more intense TC (Fig. ~~3). All locations, however, exhibit low~~ 3). Exponential fits are only shown for subsequent figures since for all figures, linear and exponential fits were found to ~~moderate correlation coefficients, though the relationship is statistically significant. These results also indicate that SLP~~ be very similar, as was seen in figure 2. The lowest RSE is seen at Portland, ME, Boston, MA, and Key West, FL. As seen in figure 2 with TC proximity, figure 3 indicates a similar conclusion, in which TC intensity alone ~~is~~does not ~~a good enough predictor of~~fully explain the variability in storm surge. ~~However, the larger~~For some locations, such as Sandy Hook, NJ, Sewell's Point, VA, and Duck, NC, the ~~correlation~~lower RSE, as compared to the ~~distance~~TC proximity analysis, ~~for most locations~~ would indicate that there is value added by examining the intensity of TCs in addition to ~~distance~~TC proximity. We also examined the time rate of change in the ~~SLP~~MSLP of TCs and found that ~~it was not~~ there was considerable variability from case-to-case and no strong statistical relationship. When examining storm surge as a ~~better predictor of surge as compared to~~function of MSLP for ET TCs, the ~~full SLP (not shown).~~fit worsens slightly for Portland, ME, Boston, MA, and Newport, RI, but improves slightly for New York, NY, Sandy Hook, NJ, and Cape May, NJ (S3). This analysis highlights the complexities associated with the change in storm dynamics as a TC transitions into an ETC.


Portland, ME
Number of TCs: 83
r = -0.5728
Boston, MA
Number of TCs: 102
r = -0.5550
Newport, RI
Number of TCs: 108
r = -0.4683
New York, NY
Number of TCs: 115
r = -0.4569
Sandy Hook, NJ
Number of TCs: 117
r = -0.4726
Cape May, NJ
Number of TCs: 85
r = -0.5207
Sewells Point, VA
Number of TCs: 145
r = -0.4962
Duck, NC
Number of TCs: 87
r = -0.5672
Charleston, SC
Number of TCs: 135
r = -0.4278
Fort Pulaski, GA
Number of TCs: 119
r = -0.4421
Fernandina Beach, FL
Number of TCs: 133
r = -0.4738
Key West, FL
Number of TCs: 104
r = -0.3375
Storm Surge (m)
Mean Sea Level Pressure (hPa)

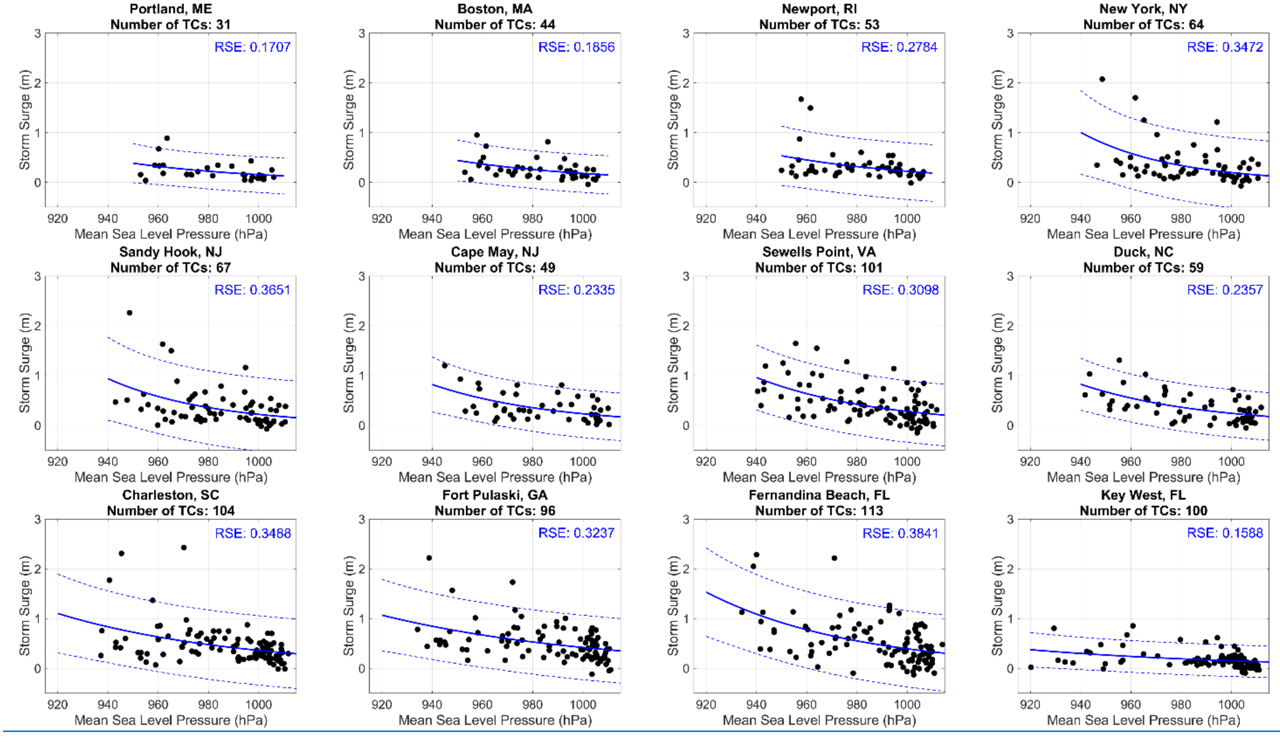
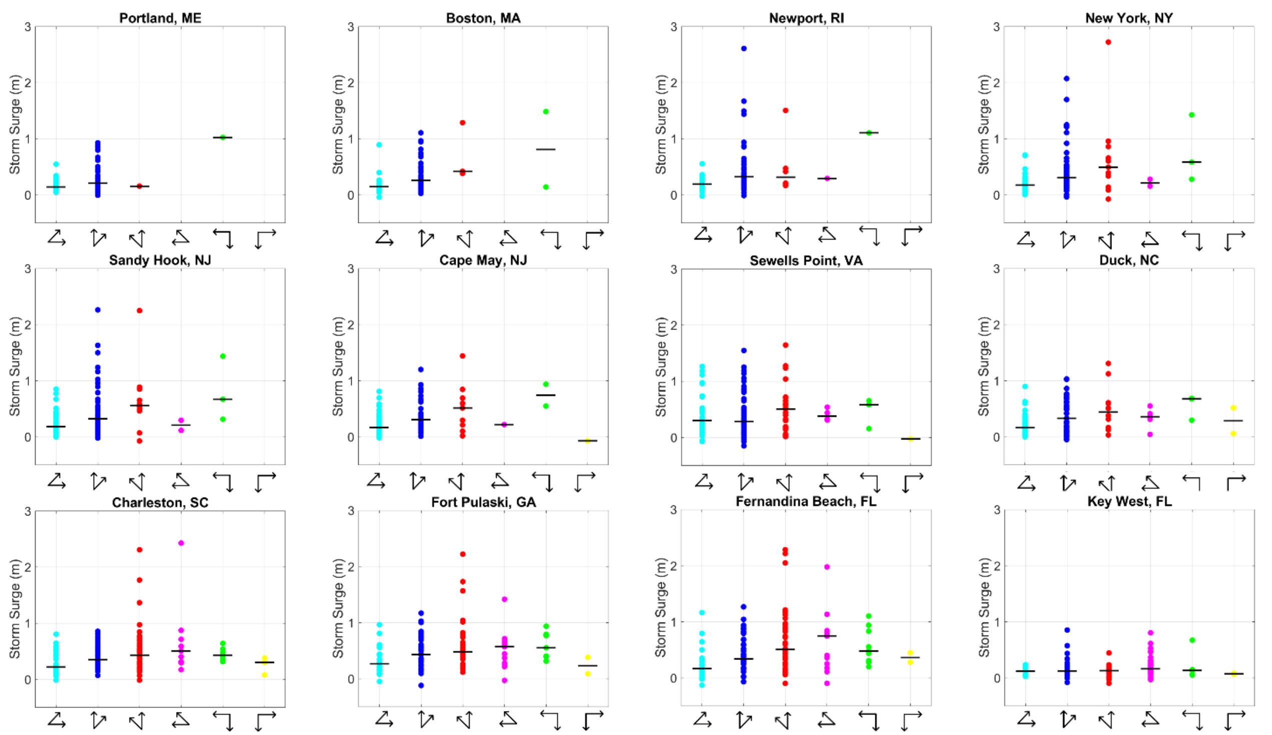

Portland, ME
Number of TCs: 31
RSE: 0.1707
Boston, MA
Number of TCs: 44
RSE: 0.1856
Newport, RI
Number of TCs: 53
RSE: 0.2784
New York, NY
Number of TCs: 64
RSE: 0.3472
Sandy Hook, NJ
Number of TCs: 67
RSE: 0.3651
Cape May, NJ
Number of TCs: 49
RSE: 0.2335
Sewells Point, VA
Number of TCs: 101
RSE: 0.3098
Duck, NC
Number of TCs: 59
RSE: 0.2357
Charleston, SC
Number of TCs: 104
RSE: 0.3488
Fort Pulaski, GA
Number of TCs: 96
RSE: 0.3237
Fernandina Beach, FL
Number of TCs: 113
RSE: 0.3841
Key West, FL
Number of TCs: 100
RSE: 0.1588
Storm Surge (m)
Mean Sea Level Pressure (hPa)

Figure 3. ~~Linear~~Exponential fit (~~red~~blue solid line) between storm surge (m) and ~~mean sea level pressure~~MSLP (hPa) with 95 % confidence intervals (dashed ~~magenta~~ line) for all TCs within 500 km. ~~Correlation coefficient, r,~~Residual standard error (RSE) is provided ~~at each site and is bold if it is statistically significant~~for the exponential fit.

The path that a TC takes relative to each location is also likely to influence the magnitude of the resulting storm surge. This would be due to the direction of the onshore winds ~~toward the coastline~~ around the TC toward a tide gauge that can greatly influence storm surge. Figure 4 shows how the magnitude of storm surge varies based on the angle of the TC track relative to each location around the time of storm surge event for all TCs within 500 km~~ of a site~~. The TCs near the most northern sites along the New England coastline (e.g., Portland, ME and Boston, MA) almost exclusively move toward the northeast. ~~As latitude decreases~~For locations at lower latitudes, the range of track paths grows, with more TCs moving toward the northwest and southwest, especially for locations south of Sewell's Point, VA. For locations north of Cape May, NJ, the largest storm surge events tend to be associated with TCs that move toward the northeast, with the exception being during Hurricane Sandy~~,~~ (not shown, since this TC was classified as extratropical), a TC which was known for its unique track (Hall and Sobel, 2013). For most locations, however, there is not a significant difference in the ~~average~~median storm surge between different track paths~~.~~ (Fig. 4). The starkest difference in storm surge based on track path is seen in Fernandina Beach, FL, where TCs moving toward the east-northeast have a median storm surge of 0.~~17~~23 m, whereas TCs moving toward the west-northwest have a median storm surge of 0.~~74~~57 m.



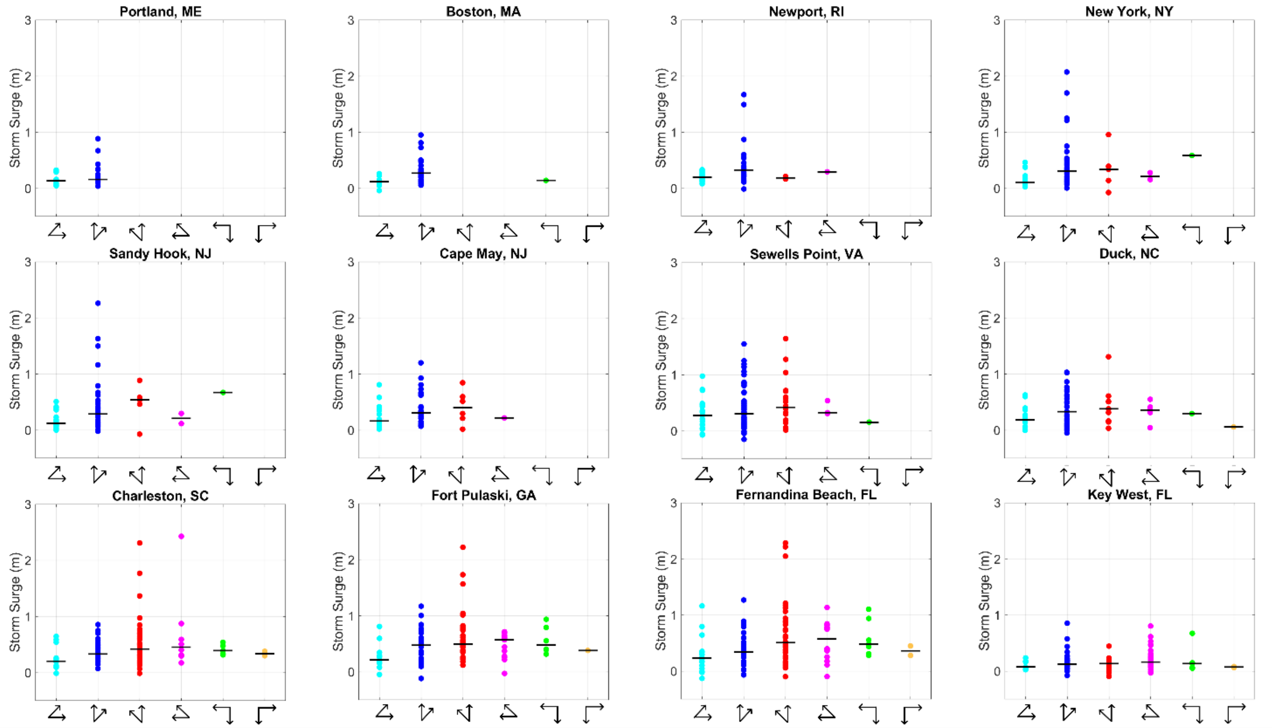
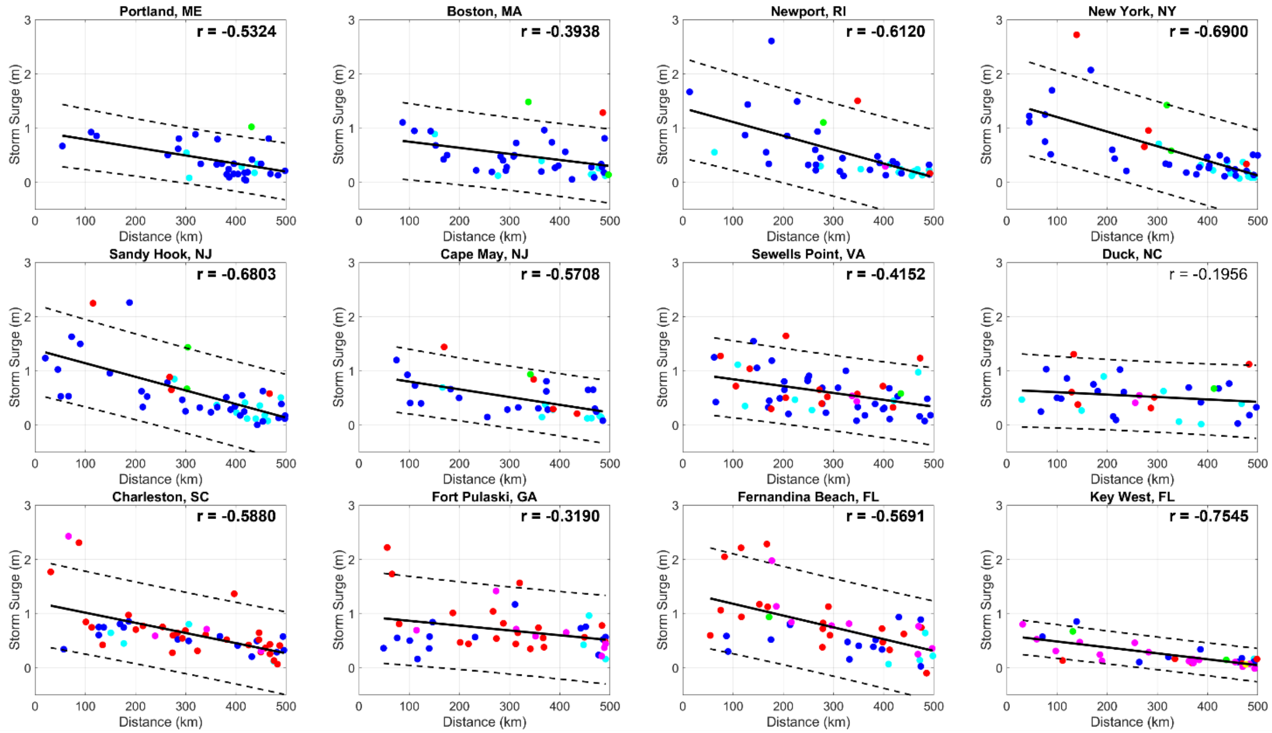


Figure 4. Storm surge (m) separated by track path angle. Arrows along x-axis indicate range of TC track movement and is similar to track path angle key in ~~Fig.~~figure 1. From left to right, arrows correspond to ENE (light blue), NNE (dark blue), NNW (red), WNW (magenta), SW (green) and SE (~~yellow~~orange). Horizontal black line indicates the median value of storm surge for each group of track path angles.

Individually, we have shown how the magnitude of storm surge varies based on TC ~~distance~~proximity, intensity, and track path. We also examined the influence of propagation speed (~~not shown~~S4) and found a negligible correlation ~~between it and~~with storm surge. Next, we use conditional sorting to explore if a stronger relationship exists among these TC characteristics with storm surge.

To see how the combination of these variables can influence the predictability of storm surge, we examine how the magnitude of storm surge correlates against distance for only TCs that ~~have a SLP less~~are stronger than ~~or equal to~~ the climatological average ~~SLP of~~MSLP for all TCs within 500 km of a site which, hereafter are referred to as strong TCs (Fig. 5). The average ~~SLP~~MSLP is calculated for each location and is provided in Table 1. The strongest relationship is seen in Boston, MA and Key West, FL~~, whereas a nearly negligible relationship~~. Each data point in figure 5 is ~~seen at Duck, NC. Figure 5 also shows~~color coded based on the average track path angle for each storm surge event. For strong TCs, most locations show no discernible relationship with track path angle ~~for~~when analyzing storm surge and distance. For both New York, NY and Sandy Hook, NJ, which are closely located to one another, TCs that move toward the east-northeast are often associated with lower storm surge and are further away, whereas TCs that move toward the north-northeast occur at all distances and subsequently result in storm surge of both low and high magnitudes. We also used conditional sorting to examine how the magnitude of storm surge correlates with ~~SLP~~MSLP for only TCs within 250 km (~~not shown~~S5) and saw a similar improvement in the ~~correlation~~fit as shown in this analysis. Conditional sorting based on ~~track~~TC path angle and, separately, ~~track~~TC propagation speed, did not ~~lead to improved correlations~~show a statistical relationship between TC ~~distance~~proximity and surge ~~(not shown).~~.



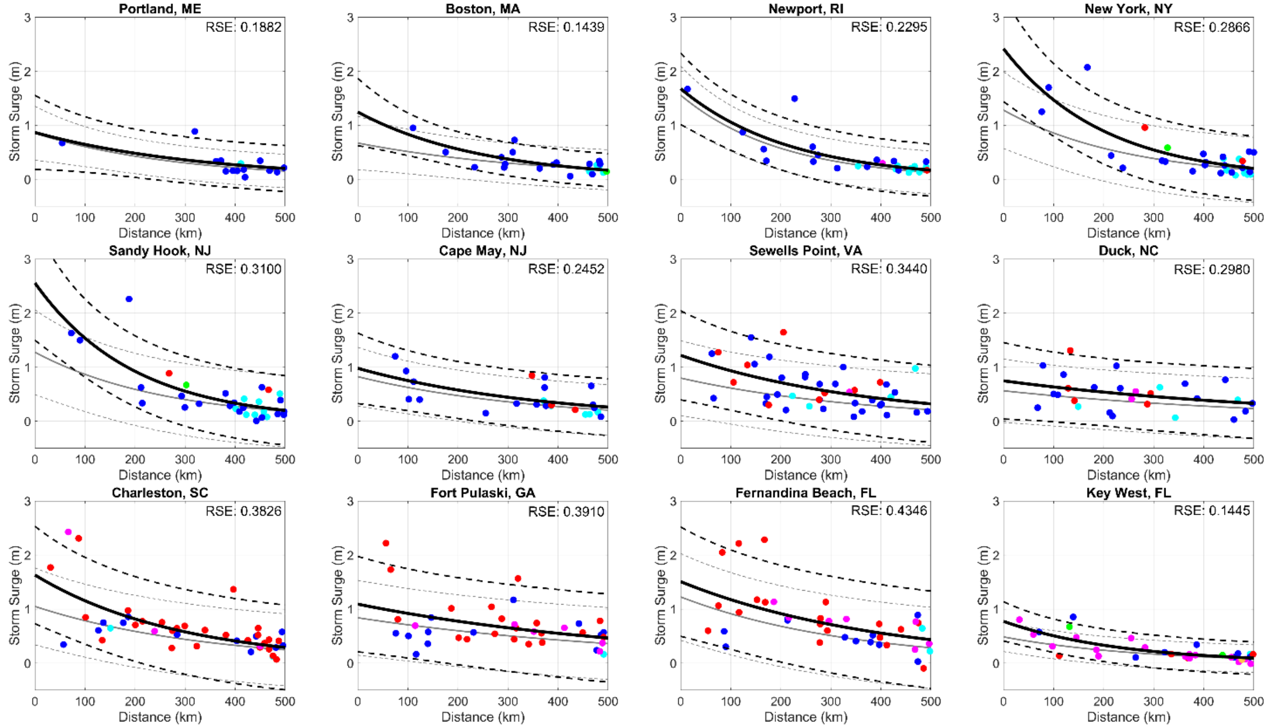


Figure 5. ~~Linear~~Exponential fit (black solid line) between storm surge (m) and ~~distance of~~ TC ~~from site~~proximity (km) for only ~~TCs whose mean sea-level pressure was less than or equal to the average mean sea-level pressure of all TCs~~ strong TCs within 500 km with 95 % confidence intervals (dashed black line~~)~~). Exponential fit (gray solid line) and 95 % confidence intervals (dashed gray line) from Figure 2 is also included for comparison to all TCs ~~within 500 km. Points~~regardless of intensity. Data points are color coded based on average track path angle as outlined in ~~Fig.~~Figure 4. ~~Correlation coefficient, r,~~Residual standard error (RSE) is provided ~~at each site and is bold~~for the exponential fit.

To complement the exponential fit analysis shown in Figures 2 - 5, we next examine correlation coefficients based on linear fits. In our linear regression analysis, we explore how the statistical fit changes if ~~it is statistically significant.~~

we consider multiple predictors and/or conditional sorting of the data. A comparison of the ~~correlations~~relationships between surge and ~~distance~~TC proximity (Fig. 2) and those for surge and ~~distance~~TC proximity after conditionally sorting to isolate for stronger TCs (Fig. 5) indicates that many locations ~~have~~exhibit an increase in their correlation coefficient. Table 3 ~~contains~~displays the correlation coefficients for individual, combined, and conditionally sorted variables in their ability to predict storm surge at each location. Each location exhibits a negative correlation that is statistically significant ($p < 0.05$) at all sites based on the method described in Section 2.2 between storm surge and both TC proximity and intensity. While the relationships are statistically significant, ~~distance and SLP, individually, do not have a strong~~the strength of the relationship of surge with ~~storm surge for TCs within 500 km of a~~TC proximity and intensity, individually, varies based on location. ~~Some~~Most locations~~, such as New York, NY, Sandy Hook, NJ, Charleston, SC, Fernandina Beach, FL, and Key West, FL,~~ exhibit a higher correlation with TC proximity than TC intensity. Only Sewell's Point, VA, Duck, NC, and Fort Pulaski, GA exhibit a higher correlation with ~~distance~~TC intensity than ~~SLP~~TC proximity. When ~~distance~~TC proximity and ~~SLP~~intensity are combined as predictors of surge, the correlation increases compared to the correlation for the variables individually and are statistically significant ($p < 0.05$) for all locations. If we isolate only TCs that are considered strong (i.e., ~~SLP~~MSLP is less than or equal to the average ~~SLP~~MSLP of all TCs within 500 km of a site) and then examine the predictability of storm surge based on ~~distance~~TC proximity, we see that the correlation increases and is statistically significant ($p < 0.05$) for all locations except Duck, NC (Table 3, Column 5).

Table 3. Correlation coefficients from linear analysis of storm surge with ~~distance, mean sea-level pressure~~TC proximity, TC intensity, combination of ~~distance~~TC proximity and ~~mean sea-level pressure~~intensity, and ~~distance~~TC proximity for only strong TCs ~~whose mean sea-level pressure was less than or equal to the average mean sea-level pressure of all TCs within 500 km. Bold~~. Correlation coefficients ~~indicate the relationship is~~that are not statistically significant are italicized.

Location	~~Distance~~TC Proximity	~~SLP~~TC Intensity	~~SLP+Distance~~TC Proximity and Intensity	~~Distance using~~TC Proximity for only strong ~~SLP only~~TCs
Portland, ME	-0.~~2850~~65	-0.~~5728~~43	-0.~~6340~~70	-0.~~5324~~66
Boston, MA	-0.~~3030~~43	-0.~~5550~~41	-0.~~6017~~57	-0.~~3938~~70
Newport, RI	-0.~~4087~~65	-0.~~4683~~35	-0.~~5950~~73	-0.~~6120~~77
New York, NY	-0.~~5271~~62	-0.~~4569~~41	-0.~~6633~~71	-0.~~6900~~77
Sandy Hook, NJ	-0.~~5306~~58	-0.~~4726~~41	-0.~~6648~~69	-0.~~6803~~75
Cape May, NJ	-0.~~4152~~52	-0.~~5207~~48	-0.~~6340~~66	-0.~~5708~~60
Sewell's Point, VA	-0.~~3670~~45	-0.~~4962~~56	-0.~~6000~~68	-0.~~4152~~48
Duck, NC	-0.~~2470~~35	-0.~~5672~~58	-0.~~5891~~62	*-0.~~1956~~34*
Charleston, SC	-0.~~4347~~46	-0.~~4278~~42	-0.~~6091~~63	-0.~~5880~~61
Fort Pulaski, GA	-0.~~3066~~37	-0.~~4421~~43	-0.~~5329~~55	-0.~~3190~~39
Fernandina Beach, FL	-0.~~5252~~54	-0.~~4738~~48	-0.~~6708~~68	-0.~~5691~~57
Key West, FL	-0.~~6411~~64	-0.~~3375~~37	-0.~~6943~~70	-0.~~7545~~75

3.2 Storm surge exceedance probabilities

In considering impacts and coastal disaster planning, hazards are often ranked using return periods. These metrics provide timescales that help in conceptualizing the potential magnitudes of the hazards, and therefore we have analyzed the return periods for the storm surge events at our study locations. Herein we report on the relationship between the return periods and the TC characteristics~~,~~ using conditional sorting that builds on the lessons learned from our regression analysis in the previous section.

We ~~calculated~~calculate return levels for various return periods for each location (Table 2) using the peaks-over-threshold method as previously ~~defined~~described in Section 2.2. Return levels are calculated using ~~hourly~~daily storm surge values for each location for all times during the year. In our analysis, we focus on the ~~0.5-year~~1-yr return level, which would mean on average, a location could expect to experience ~~two~~one storm surge ~~events~~event of this magnitude each year (or each hurricane season).

Using the ~~0.5-year~~1-yr return levels, we seek to determine the probability of storm surge exceeding this threshold, conditional on certain TC characteristics (Table 4). First, we examine the probability of TCs within a specific distance resulting in storm surge exceeding the ~~0.5-year~~1-yr return level. As the distance decreases from 500 km to 100 km, the percentage of TCs ~~creating~~producing storm surge ~~exceeding~~that exceeds the ~~0.5-year~~1-yr return level increases. This would indicate that as a TC gets closer, the likelihood that it produces high surge is greater than if it were at a further distance. At a distance of 250 km, less than ~~10~~15 % of TCs have resulted in storm surge that exceeds ~~at least~~ the ~~0.5-year~~1-yr return level at ~~the~~ two of the three most northern sites, ~~Portland, ME and~~ Boston, MA, and Newport, RI, as well as Duck, NC (Fig. 6a). Three of the four most southern sites, including Charleston, SC, Fernandina Beach, FL, and Key West, FL, have experienced more than 30 % of TCs within 250 km resulting in storm surge exceeding the ~~0.5-year~~1-yr return level, with ~~almost~~over 50 % at Key West, FL.

Table 4. Percentages for each location of TCs within 500 km, 250 km, and 100 km under two criteria: 1) within a specified distance that ~~exceeded 0.5~~produced surge exceeding 1-yr return level and b) within a specified distance and whose ~~mean sea level pressure~~MSLP is less than or equal to the average ~~mean sea level pressure~~MSLP of all TCs within a specified distance that ~~exceeded 0.5~~produced surge exceeding 1-yr return level. The number of individual TCs that met all criteria is given by "N" and the total number of TCs that met the distance and/or intensity criteria but did not exceed the return level is given by the bracketed number. The "N" number divided by the bracketed number will give the percentage in the same box.

Location	~~If a storm is~~For TCs within X distance, how many ~~result in 0.5~~produce surge exceeding 1-yr return level?			~~If a storm is~~For strong TCs within X distance ~~and the TC has SLP less than or equal to the mean SLP~~, how many ~~result in 0.5~~produce surge exceeding 1-yr return level?		
	500 km	250 km	100 km	500 km	250 km	100 km
Portland, ME	~~9.64~~ 6.45%	~~10~~ 18.18%	~~14.29~~ 50.00% N = 1 [~~7~~2]	~~23.53~~ 13.33% N = ~~8 [34~~2 [15]	~~30~~ 50.00% N = ~~3 [10~~2 [4]	~~50~~ 100.00% N = 1 [~~2~~1]

	N = ~~8 [83~~2 [31]	N = ~~3 [30~~2 [11]				
Boston, MA	~~7.84~~ 6.82% N = ~~8 [102~~3 [44]	~~5.56~~ 12.50% N = 2 [~~36~~16]	~~10~~ 20% N = 1 [~~10~~5]	~~20.51~~ 13.04% N = ~~8 [39~~3 [23]	~~16.67~~ 28.57% N = 2 [~~12~~7]	~~33.33~~ 50.00% N = 1 [~~3~~2]
Newport, RI	~~9.26~~ 7.55% N = ~~10 [108~~4 [53]	11.~~36~~ 54% N = ~~5 [44~~3 [26]	~~15.38~~ 25.00% N = 2 [~~13~~8]	~~21.43~~ 14.29% N = ~~9 [42~~4 [28]	~~31.25~~ 23.08% N = ~~5 [16~~3 [13]	~~40~~ 66.67% N = 2 [~~5~~3]
New York, NY	~~9.57~~ 7.81% N = ~~11 [115~~5 [64]	~~18.42~~ 20.83% N = ~~7 [38~~5 [24]	~~20~~ 25.00% N = 3 [~~15~~12]	~~17.78~~ 12.12% N = ~~8 [45~~4 [33]	~~38.46~~ 36.36% N = ~~5 [13~~4 [11]	40~~-~~.00% N = 2 [5]
Sandy Hook, NJ	~~11.11~~ 7.46% N = ~~13 [117~~5 [67]	20~~-~~.83% N = ~~8 [40~~5 [24]	~~18.75~~ 25.00% N = 3 [~~16~~12]	~~21.28~~ 11.43% N = ~~10 [47~~4 [35]	~~38.46~~ 36.36% N = ~~5 [13~~4 [11]	33.33~~-~~% N = 2 [6]
Cape May, NJ	~~10.59~~ 12.24% N = ~~9 [85~~6 [49]	~~13.51~~ 15.79% N = ~~5 [37~~3 [19]	~~14.29~~ 0.00% N = ~~1 [7~~0 [4]	~~21.88~~ 20.00% N = ~~7 [32~~5 [25]	~~26.67~~ 25.00% N = ~~4 [15~~3 [12]	~~33.33~~ 0.00% N = ~~1 [3~~0 [2]
~~Sewells~~Sewell's Point, VA	~~21.38~~ 15.84% N = ~~31 [145~~16 [101]	~~23.17~~ 21.82% N = ~~19 [82~~12 [55]	~~25.93~~ 16.67% N = ~~7 [27~~3 [18]	~~37.04~~ 27.91% N = ~~20 [54~~12 [43]	~~37.93~~ 34.62% N = ~~11 [29~~9 [26]	~~45.45~~ 33.33% N = ~~5 [11~~3 [1]
Duck, NC	~~17.24~~ 16.95% N = ~~15 [87~~10 [59]	~~10.91~~ 14.29% N = ~~6 [55~~5 [35]	~~11.11~~ 8.33% N = ~~2 [18~~1 [12]	~~38.24~~ 33.33% N = ~~13 [34~~9 [27]	~~20~~ 29.41% N = ~~4 [20~~5 [17]	~~16.67~~ 20.00% N = 1 [~~6~~5]
Charleston, SC	~~25.93~~ 27.88% N = ~~35 [135~~29 [104]	~~31.08~~ 33.90% N = ~~23 [74~~20 [59]	30.~~77~~ 00% N = ~~8 [26~~6 [20]	~~51.92~~ 50.00% N = ~~27 [52~~22 [44]	~~61.29~~ 60.71% N = ~~19 [31~~17 [28]	~~75~~ 71.43% N = ~~6 [8~~5 [7]
Fort Pulaski, GA	~~24.37~~ 26.04% N = ~~29 [119~~25 [96]	~~26.56~~ 27.78% N = ~~17 [64~~15 [54]	~~27.27~~ 26.32% N = ~~6 [22~~5 [19]	~~38.64~~ 40.00% N = ~~17 [44~~16 [40]	~~43.48~~ 42.86% N = ~~10 [23~~9 [21]	42.86~~-~~% N = 3 [7]
Fernandina Beach, FL	~~23.31~~ 24.78% N = ~~31 [133~~28 [113]	~~37.88~~ 40.68% N = ~~25 [66~~24 [59]	~~38.1~~ 36.84% N = ~~8 [21~~7 [19]	~~39.13~~ 45.00% N = 18 [~~46~~40]	~~69.23~~ 68.00% N = ~~18 [26~~17 [25]	~~71.43~~ 66.67% N = ~~5 [7~~4 [6]

Key West, FL	24.04 26.00% N = 25 [10426 [100]	48.84 52.38% N = 21 [4322 [42]	50 55.56% N = 910 [18]	33.33 34.38% N = 11 [3332]	61.54 % N = 8 [13]	71.43 % N = 5 [7]

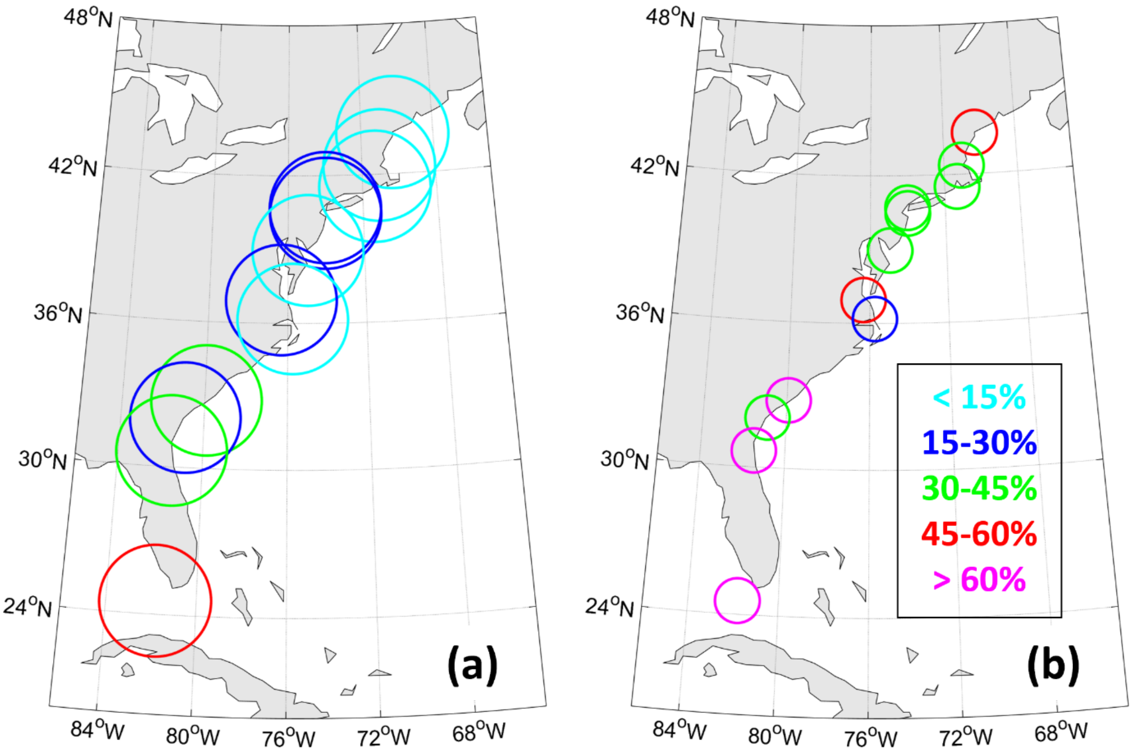


Figure 6: Visual depiction of data from table 4 for percentage of TCs a) within 250 km that exceed 0.5-yr return level and b) within 100 km and whose mean sea-level pressure is less than or equal to the average mean sea-level pressure of all TCs within 100 km. Size of circles indicates the search radius around each location and is color coded based on the percentage value with <15 % (light blue), 15-30 % (dark blue), 30-45 % (green), 45-60 % (red), and >60 % (magenta).

From our analysis in Section 3.1, we found that distance alone is not sufficient when considering itsthe effect of a TC on the magnitude of storm surge. Therefore, we next report on the probability of TCs within a specific distance and with a specific intensity. Because the average TC SLPintensity varies across our study location, instead of using a fixed SLPintensity threshold to sort the TCs, we use the average SLPintensity of all TCs within a specified distance per site. Herein we focus on the TCs with SLPMSLP lower than the site averages. At, i.e., the strongest 50th percentile of TCs per site. At the smallest distance threshold analyzed, 100 km, all locations with the exception of Cape May, NJ and Duck, NC have at least a third of all TCs resulting in storm surge exceeding the 0.5-year1-yr return level. Similar to before, three of the four most southern sites, including Charleston, SC, Fernandina Beach, FL, and Key West, FL have experienced more than ~~70~~67 % of all TCs resulting in storm surge exceeding the ~~0.5-year~~1-yr return level (Fig. 6b). ~~Since Duck, NC is~~In addition to these locations, however, the ~~only location that sees a decrease in the probability~~three most northern locations, Portland, ME, Boston, MA, and Newport, RI experienced at least 50% of ~~strong~~all TCs resulting in storm surge exceeding the ~~0.5-year~~1-yr return level~~ as distance decreases, we examined~~. While the ~~tracks~~number of ~~these~~ TCs ~~within each distance of 500~~that are considered both close (< 100 km) and ~~250 km (not shown). From~~strong are small at these high latitudes, this~~, we can conclude~~ analysis shows that these types of TCs at these latitudes may result in high surge if they meet this ~~decrease in TC probability at Duck, NC cannot be explained by the TC track paths themselves as TCs within 250 km take similar paths as those within 500 km. Additionally, most of the TCs that move near Duck, NC do not pass over land and instead move parallel to the coastline or remain further out to sea~~criteria.

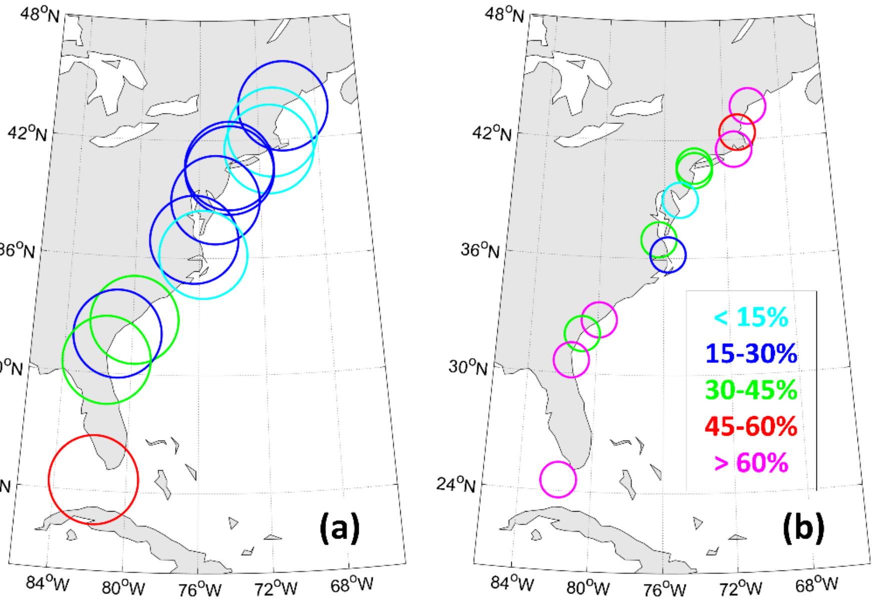


Figure 6. Percentage of TCs that produce surge exceeding the location's 1-yr return level and: a) are within 250 km; b) are within 100 km and whose MSLP is less than or equal to the average MSLP of all TCs within 100 km. Size of circles indicates the search radius around each location. Color coding is based on the percentage value with <15 % (light blue), 15-30 % (dark blue), 30-45 % (green), 45-60 % (red), and >60 % (magenta).

While ~~distance~~proximity and ~~the~~ intensity of the TCs are important factors in predicting storm surge, we cannot ignore the role of the TC path angle ~~of the TC track~~ relative to each location~~.~~ around the time of the surge maximum. While we have shown that some locations experience TCs from a specific range of angles (Fig. ~~4), that track~~4), TC tracks with similar path angles can end up passing by a location in a different quadrant ~~where,~~relative to the tide gauge; for example, a TC could pass to either the northwest or southeast of Charleston, SC, but have similar track path angles. In this scenario, one TC would track over land while the other TC would track over the open water. This difference could impact the structure of the TC, including its intensity and the direction ~~that~~of the winds ~~are blowing~~relative to the tide gauge, all of which might impact the magnitude of the storm surge. ~~We~~To consider this~~ and examined~~, we examine TC locations and the intensity of the TC at the time of the surge maximum (~~not shown). However~~Fig. 7). For this figure, note that: (1) color now represents the strength of the TCs around the time of the surge maximum, and (2) because the surge is hourly and the TC locations are 6-hourly, the point of maximum surge for a TC corresponds to the 6-hourly time that is closest to the surge maximum. For locations north of Sewell's Point, VA, there ~~was no~~is a clear ~~relationships among~~difference in tracks of strong TCs that do and do not produce surge that exceeds the 1-yr return level. For TCs that do produce surge exceeding the 1-yr return level, these ~~variables but they do warrant~~TCs are much stronger than the average TC and take a more meridional path whereas TCs that do not produce high surge are weaker and/or recurve out to sea. The highest surge for TCs that produce surge exceeding 1-yr return levels also generally occurs when the TC is located to the southwest of each location, allowing for onshore winds to push water towards the coastline. For locations that are further ~~examination in future analysis of storm surge and TC characteristics~~south, the picture is more complicated as TCs approach from different directions. For these southern locations, there seems to be greater dependence on TC intensity than on TC path angle. While a majority of the TCs that produce surge exceeding the 1-yr return levels at Charleston, SC, Fort Pulaski, GA, and Fernandina Beach, FL generally move in a north-westward direction over Florida, nearly all of them have an average intensity around the time of surge maximum of 980 hPa or less.

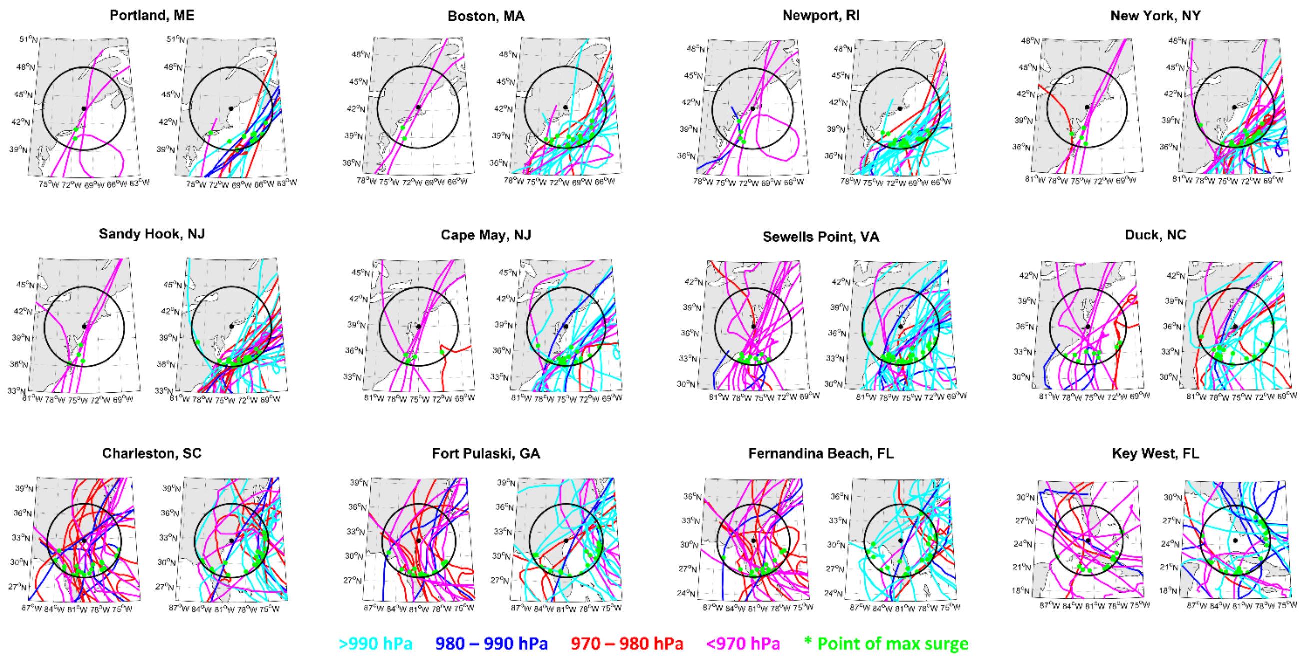


Figure 7. For each location, strong TC tracks for those TCs that do result in surge exceeding 1-yr return level (left) and those that do not (right). Tracks are color coded based on average MSLP as follows: > 990 hPa (light blue), 980 - 990 hPa (dark blue), 970 -

980 hPa (red), and < 970 hPa (magenta). Black circle represents 500 km radius. Green dots represent closest TC location at time of surge maximum.

4 Conclusion

This study ~~used~~uses observations to examine the predictability of storm surge based on the following TC characteristics: ~~the distance of the~~ TC ~~center from a site as well as its~~proximity, intensity, ~~track~~ path angle, and propagation speed. At each ~~location~~tide gauge along the east coast of the US, storm surge is influenced differently by these TC characteristics, with some locations more strongly influenced by TC intensity (e.g., ~~New York, NY, Charleston, SC~~Sewell's Point, VA, Duck, NC, and ~~Key West, FL) and others~~Fort Pulaski, GA), but most sites more strongly influenced by ~~the distance of the~~ TC ~~center to each site (e.g., Boston, MA, Cape May, NJ, and Sewell's Point, VA).~~proximity. All locations except Duck, NC see an increase in the correlation of ~~the distance from the TC~~TC proximity with storm surge once only strong TCs are considered.

When correlating storm surge with TC characteristics, ~~all individual variables display a statistically significant low to moderate correlation, which indicates the complicated (i.e., statistically noisy) nature of relationships between the TCs and the surges they drive.~~we found the following for single-variable correlations: TC propagation speed does not have statistically significant relationships with surge amplitude; TC proximity and intensity both have a statistically significant ($p < 0.05$) but low to moderate correlation; TC path angle has a conditional dependence, but only at some locations. Taken together, the results indicate that storm surge produced by TCs cannot be fully explained by one TC characteristic. This result reinforces the natural variability of TCs, such that each TC is unique in its shape, size, speed, and location. Thus, it is challenging to find a strong correlation between storm surge and individual TC characteristics. For most sites, the highest storm surge occurs when a TC is within ~~200~~250 km of a site and the TC intensity is strong. This~~,~~ at least~~,~~ affirms the natural assumption that a TC that is both close to a site and strong has the greatest chance of resulting in ~~strong~~high storm surge. Related to this point: when comparing all TCs within 500 km to those TCs considered strong within 500 km, the correlation increased for all locations except Duck, NC. ~~The site at Duck, NC is unique from the other locations because it is not near or in a bay or harbor. The track path angle and propagation speed contribute very little to the overall correlation among all variables for all sites.~~

When we consider all TCs that pass within 500 km of a site, the percentage of TCs that cause surge exceeding the ~~0.5~~1-yr return level is between ~~7~~6 % and ~~26~~28 %, with the higher percentages at the more southern sites. For a 100 km search radius, the percentage of TCs generating storm surge exceeding the ~~0.5~~1-yr return level ~~are~~is larger at nearly all sites~~. For sites in Florida,~~, with the ~~percent increase is greatest, from 14 % to 26 %. For all other locations, the increase is between 2 %~~exception of Cape May, NJ and ~~10 %. Interestingly, for~~ Duck, NC, ~~the percent of TCs creating surge exceeding the 0.5-yr return level is lower for the smaller search radius. We examined if this change was due to the smaller search radius leading to~~both which exhibit a ~~larger fraction of the associated TCs being over land, and that is not the case. Nor is it the case that the distribution of track path angles for the smaller radius differ significantly from that for the larger radius. Thus, the difference is likely related to coastal orientation or chance.~~

decrease. If we consider only the strongest TCs, ~~most~~almost all sites ~~see~~have an increase in the probability of a ~~0.5~~1-yr surge exceedance~~ for a search radius of 500 km compared to 100 km. ~~. Cape, May, NJ and Duck, NC ~~is~~are again ~~an exception~~exceptions, signifying that other ~~variables~~factors must play ~~a more~~an important role in storm surge generation. The site at Duck, NC is unique from the other locations because it is not near or in a bay or harbor. Meanwhile the site at Cape May, NJ is unique because it is on southern edge of a peninsula abutting the Delaware Bay. For sites that are farther south, there is a greater likelihood that TCs that pass within a fixed distance of a site will generate storm surge that exceeds the ~~0.5~~1-yr return level~~, which is consistent with the fact~~. One reason for this is that TCs reach their maximum strength at lower latitudes. Another issue to consider is that for the northern sites, ETCs have a larger influence in setting the amplitude of the surge returns levels (e.g., Booth et al. 2016). With this in mind, we have started a new analysis that considers the implications of separating TCs and ETCs in probabilistic assessments.

The full complexity of the relationship between TCs and storm surge becomes apparent when we conditionally sort, based on TC intensity, the paths of TCs that do and do not generate surges that exceed the 1-yr return levels per site (Fig. 7). For some locations, there is a suggestion of a relationship with TC distance and track path angle (e.g., Newport, RI), while for other sites, the path seems less relevant than the TC intensity (e.g., Fernandina Beach, FL). Overall, the story of this analysis is three-fold: (1) using single and multi-variable regression to predict TC-generated surge in the observational record provides a good but not great fit; (2) TC proximity and intensity are better predictors than TC path angle or propagation speed, and (3) when a strong TC passes within 100 km of a location, there is always at least a 1-in-3 chance that it will generate at least an exceedance of the 1-yr return level – with two site exceptions that depend strongly on coastal geometry.

Before starting this study, we hypothesized that (based on basic physics): TC intensity would have a strong relationship with storm surge, if we were able to isolate ~~TC~~ cases in which other ~~cyclone~~TC characteristics were similar. Ultimately, we found that isolating "the same type" of TC is not simple. For the southernmost sites, the relationships are more obvious, and that is possibly due to the larger sample size. For the more northern sites, one might consider testing the hypothesis using numerical modelling, ~~which to our knowledge, has not been done yet. For instance,~~in which one could model a single TC and synthetically change details of the storm~~.~~, as done previously by Lin et al. (2010), Garner et al. (2017), and Ramos-Valle et al. (2020). However, we want to emphasize that such an approach is very different from our work herein, because in the ~~observations~~observational dataset it is not possible to ensure that only one characteristic of a TC varies while all others remain constant.

While many studies have focused on the utilization of numerical models to understand the relationship between TC characteristics and storm surge, this study ~~takes~~uses historical observations~~ for 12 sites~~ along the east coast of the US to assess the relationship between TC characteristics and storm surge. This type of analysis allows us to understand the current relationship between TC characteristics and storm surge so that this information can be applied to the understanding of how storm surge and subsequently, the characteristics of TCs, may change under a warming climate. While no single TC characteristic determines how much surge will be generated, this analysis does offer a unique perspective on the probabilities of surge events associated with all TCs rather than only those that cause extreme surge. This analysis, while limited to the east coast of the US, can ~~easily~~ be applied to any ~~location~~region with a record of not only surge observations, but other hazards, such as precipitation or wind, while also being used in conjunction with any cyclone dataset, including ETCs and transitioning cyclones.

Data Availability. Water level data that is used for the calculation of storm surge is publicly available and can be accessed at https://tidesandcurrents.noaa.gov/. Dataset of tropical cyclones is also publicly available and can be accessed at https://www.nhc.noaa.gov/data/.

Author contribution. KT wrote the manuscript with input from JB, ARE, and TW. JB downloaded data and calculated surge. KT completed data analysis and analyzed results with JB, ARE, and TW. JB provided code framework for cyclone association code. ARE provided code framework for calculation of return levels.

Competing interests. The authors declare that they have no conflict of interest.

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