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Tropical Cyclone Storm Surge Risk

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Abstract Tropical cyclone storm surge represents a significant threat to communities around the world. These surge characteristics vary spatially and temporally over a range of scales; therefore, conceptual frameworks for understanding and mitigating them must be cast within a context of risk that covers the complete range of hazards, their consequences, and methods for mitigation. A review of primary overlapping time scales and associated spatial scales for tropical cyclone surge hazards covers two scales of particular interest: (1) synoptic-scale predictions used for warnings and evacuation decisions and (2) long-term estimation of hazards and related risks needed for coastal planning and decision-making. Factors that can affect these estimates, such as episodic variations in tropical cyclone characteristics and longer-term climate change and sea-level rise are then examined in the context of their potential impacts on hazards and risks related to tropical cyclone surges.

Keywords Tropical cyclones · Storm surges · Forecasting · Climate change · Sea-level rise · Coastal hazards

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Introduction

Tropical cyclones have long been recognized as a major risk factor around the world both in terms of their damage and the number of lives they claim. However, the nature of risks posed varies considerably in different areas. Loss of life is particularly concentrated in less-developed countries in tropical and subtropical areas with low coastal plains bordering broad continental shelves. In Bangladesh alone, it is estimated that 450,000 deaths have been caused by these storms from 1970 to 2012, and in neighboring Myanmar, the death toll is estimated to be close to 140,000 over the same interval (World Meteorological Organization [WMO], 2014). In the Philippines, typhoons resulted in the loss of more than 12,000 lives over the period 1970–2012 ([90]; Philippines National Risk Reduction and Management Council [58]). Although it is difficult to quantify the causes of death very precisely, it is clear in many of these areas that coastal inundation from storm surge was the major contributor to these high death tolls. In regions with relatively steep offshore slopes and higher coastal topography, such as many Pacific and Caribbean Islands and Central America, the loss of life due to storm surge is diminished but still occurs in low-lying areas. In these regions, much of the loss of life associated with tropical cyclones is related to inland flooding and mudslides. In highly industrialized countries with good infrastructure and well-developed warning systems, the death toll tends to be lower, but damage far higher. For example, a 1991 typhoon caused $16.9 billion of damage in Japan, and in the US, direct damages due to hurricanes are estimated to be $539 billion from 1980 to 2013, adjusted to 2014 dollars [1, 73]. This is not to trivialize the loss of life due to tropical cyclones in the US. The 1833 lives lost in Hurricane Katrina (2005) alone made it the deadliest weather-related disaster during the 1980 to 2012 period [90].

From the preceding discussion, we see that global risks posed by tropical cyclones are not spatially homogeneous. Likewise, it is clear that the time scales of risks posed by these storms cover a broad range. Historically, two major thrusts to deal with these risks emerged. The first deals with the problem of predicting synoptic-scale risks (typically the prediction of migratory features on the order of 1000 km on time scales 1–5 days) and developing emergency responses to these risks (evacuations, storm preparations, etc.). The second deals with long-term planning (establishing risk zones in coastal areas, land use restrictions, etc.). It is obvious that the changing climate has the potential to affect risks on all scales; thus, a third time scale of multi-year to decadal variability is now recognized in terms of its potential impact on coastal risks. The tools and approaches used by the first two groups have developed somewhat independently. Consequently, it can be difficult to combine them into a single risk system. Davies [9] presented a systematic approach to the problem of tropical storm surge risk (Fig. 1). As can be seen in this figure, the role of different time ranges and the societal importance of weather information shift as the time and space scales increase. It is likely that all areas of the world have a continuous range of meteorological and climatological forcing that must be dealt with seamlessly to understand and quantify risks and to improve community resilience. Since the full spectrum of time scales are important in terms of tropical cyclone surge impacts, this paper will include their entire range within its scope.

Assessment of tropical cyclone surge risk requires an understanding of both the hazard and its consequence. In this review, we focus primarily on quantification of the surge hazard. Progress on storm surge hazard assessments over the last decade largely grew out of the record damage and devastation caused in US cities following Hurricanes Katrina (2005), Ike (2008), and Sandy (2012), all of which occurred in areas characterized by low coastal plains bordering broad continental shelves. Many of the recent scientific contributions to the tropical cyclone storm surge risk problem have likewise come from US-based scientists and engineers. Thus, this review accordingly emphasizes these contributions.

Estimating Tropical Cyclone Surge Hazard on the Scale of Days

Two opposing considerations exist for computational storm surge model selection for tropical cyclone synoptic-scale prediction. On one hand, it can be argued uncertainties in real-time and forecast storm characteristics justify the use of relatively crude resolution and neglect of some physical terms in

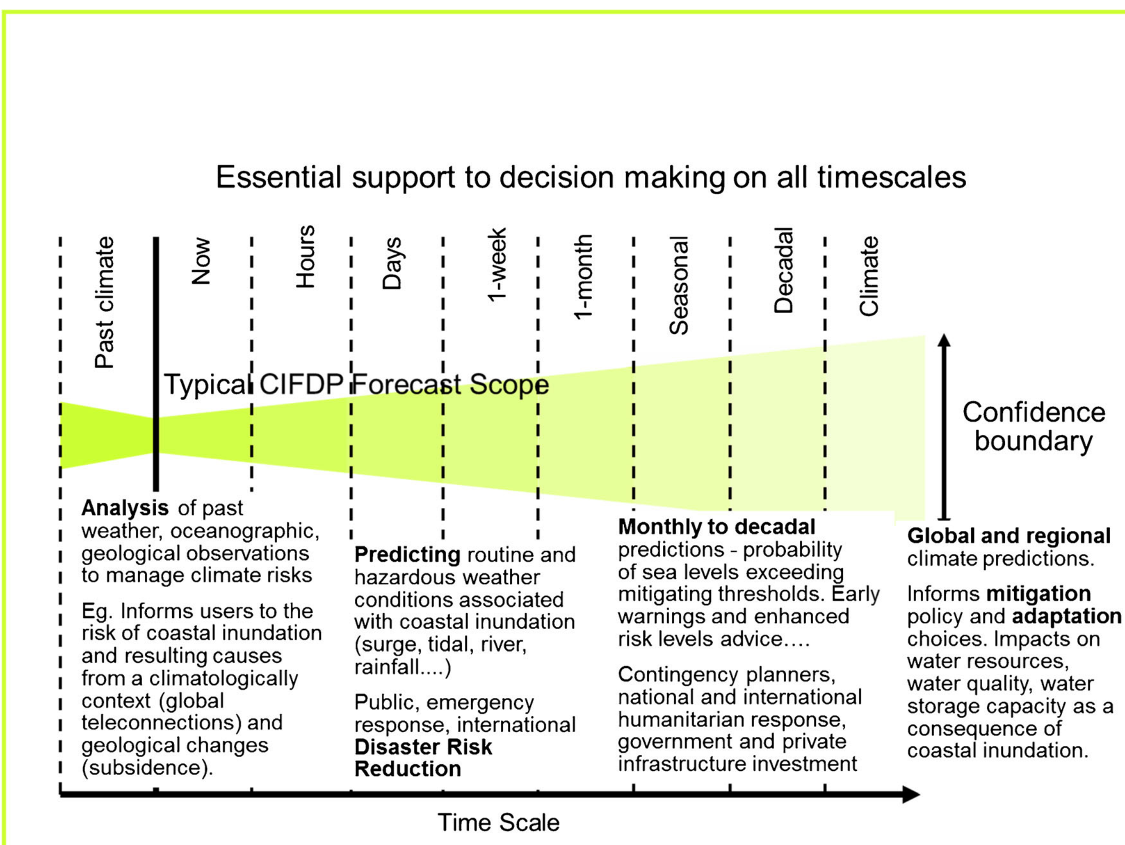

Fig. 1 Concept of information needs for decision-making over a range of time scales (modified from [9])

forecast surge simulations, e.g., the application of the SLOSH model [20] in the US. On the other hand, accurate prediction of storm surges in coastal areas, particularly inland inundation, requires high resolution and inclusion of all contributing physical processes in the simulations, such as waves along coasts typical of many Caribbean and Pacific regions [68] and the coupled influence of river flow and surges during landfall [41, 42]. Two widely used modeling suites for accurate, high-resolution surge simulation include Delft3D [10] and ADCI RC (e.g., [56, 88]), coupled with either STWAVE or SWAN (e.g., [11]). In the US, both model resolution and physics are compromised in current operational surge forecast systems to meet run-time constraints, so to some extent computational speed currently maintains a higher priority than absolute accuracy.

To provide a context for a choice in operational models, one should recognize the important distinction between random variations and bias in the effect of errors on decision-making. Randomly distributed errors in surge models with zero mean contribute by increasing uncertainty in surge predictions in addition to errors inherent in the forecasts. For random, independent forecast and surge model errors, the increase in uncertainty due to surge model errors, relative to the total error in a forecast system alone (i.e., using a surge model with no random error) is equal to $\left(1+\frac{\sigma_m^2}{\sigma_f^2}\right)^{1/2}$ where σ_m^2 is the variance of the error produced by the modeling system, and σ_f^2 is the variance of error in forecast surges related to errors in storm characteristics. Bias introduced by a systematic error inherent in a particular model introduces a systematic bias in the forecast system results, in addition to increased random error.

Wind models available for application to operational surge forecasts include analytical parametric models [26, 27, 59], steady-state dynamic models ([78, 82]), and non-steady-state dynamic models such as the Hurricane Weather Research Forecast (HWRF) model; however, the last of these is still in an experimental stage of development and is not currently used for operational purposes. The first two types of models utilize at least six parameters in their applications: storm track (landfall location), intensity (pressure differential), size (radius to maximum winds), forward speed, angle of intersection of the storm track with the coast, and the Holland B parameter (wind field peakedness; [26, 27]).

In the US, operational surge forecasts assume a different wind field approximation with an asymmetric parabolic shape [28], roughly approximating an exponential form with a constant Holland B value. In spite of this somewhat questionable form, objective testing by Houston et al. [29] concluded parametric winds at landfall reasonably represented the maximum winds in most storms studied. Estimated errors in each of the remaining five parameters can be scaled to approximate the magnitude of the associated errors in surges using response surface concepts [33, 67, 68]. Official forecast cross-track errors averaged over last 5-years are 85 and 151 km at 24 and 48 h, respectively. These estimates can be converted into surge errors for a given size storm using the results of Irish et al. [33] who showed that along-coast surges vary systematically as a function of $\frac{x-x_0}{R_{\max}}$, where x is the location of a point along the coast, x_0 is landfall location, and $R_{\max}$ is radius to maximum winds. Based on data from Vickery and Wadhera [83], about 50 % of storms have $R_{\max}$ values in the range of 35 to 55 km, yielding standard deviations in the range of 40–100 % for peak surge for a 24-h forecast and 55–100 % for a 48-h forecast. The results of Kerr et al. [41, 42] and Lin et al. [54] indicate SLOSH surges are significantly biased low at the coast for larger storms and contain relatively large random error in comparison to high water marks. Both of these comparisons used different wind field models than used operationally in SLOSH. Forbes et al. [20], using standard operational wind fields, obtained relatively unbiased results with a standard deviation of about 25 % in peak surge. For this magnitude of error, SLOSH increases surge uncertainty, over that inherent in the storm track forecast, by 3–12 % in 24-h forecasts and 2–17 % in 48-h forecasts. This impact of surge model uncertainty is equivalent to an increase in the 24-h forecast track uncertainty of about 3–10 km, and 3–15 km for the 24 and 48-h forecasts. The contribution of surge model uncertainty increases significantly as forecast time is reduced to a “nowcast,” reaching well over 50 % of the total error at landfall. All of the studies noted SLOSH appears to have some spatial bias, with accuracy becoming increasingly biased toward higher values inland. This problem is currently being researched at the National Hurricane Center [92]. Here, we only discussed the impact of errors in forecast tracks, since this is the dominant contributor to surge forecasting error. Errors in the remaining five meteorological terms will act to change the general results discussed here, but have not been studied in much detail. From this discussion, we see that the question of forecast accuracy in current forecast systems may not be too problematic until close to landfall; given the importance of accuracy as landfall approaches, this issue needs continued scrutiny.

Estimating Tropical Cyclone Surge Hazard on a Multi-year Scale

Most coastal planning considers time frames in the range of years to decades. For example, in the US, cost-benefit calculations by the US Army Corps of Engineers (USACE) for coastal programs and programs within the Federal Emergency Management Agency (FEMA) such as the National Flood Insurance Program (NFIP) consider an expected statistical behavior over a multi-year scale, as do most planning groups worldwide; so this will be the focus here. Prior to Hurricane Katrina in 2005, the flood hazard assessments transitioned from the Joint Probability Method (JPM) in the 1970s [60, 25] to a Historical Storm Method (HSM) in the 1990s [69] based on a Points Over Threshold (POT) approach combined with Monte Carlo simulations to quantify potential uncertainty. The use of Monte Carlo to quantify uncertainty provides an unbiased estimate of errors, assuming the initial estimate provides an unbiased estimate of the parent population given all quantiles of the sample match the equivalent quantiles of the parent population. Unfortunately, this type of estimate only provides information on what happened in the past and not on what can happen in the future. Hurricane Katrina provided direct evidence that there could be large discrepancies between these two types of information. As a result, since 2005, the USACE and FEMA adopted the JPM with some modifications to reduce the number of storms in the sample required for surge simulation, while maintaining good accuracy for planning purposes—sometimes termed the JPM-OS approach for "optimal sampling" [33, 67, 68, 80]. Irish et al. [34] showed the estimation power of the JPM significantly exceeds that of the HSM, and that the use of historical surge data alone for planning could introduce substantial local errors into design and planning decision-making. Figure 2 illustrates the problem with the HSM for accurately representing the surge hazard; here, the 100-year return period surge in New York City changes dramatically from 1.8 to 2.5 m (39 % increase) when Hurricane Sandy (2012) is included in the parent population.

Although the impetus of Katrina provided momentum for change and helped advance the state of the art in quantifying flood hazards in coastal areas, a similar problem emerged in the estimation of risk for planning time scales as was noted in the section on synoptic forecasting. Given the economic impacts of hazard zones on communities, higher resolution and a thorough coverage of the probability space for these simulations is even more important than for the case of forecasting. Consequently, the number of storms needed in planning simulations and their spatial resolution, combined with the need for inclusion of all physical terms in coupled surge modeling systems, makes the computational burden extremely large. A simplistic, sampling method using equal spacing across the six tropical cyclone meteorological parameters was used in early applications of the JPM [60, 25]; however, at that time, SLOSH was used in the US for estimating the long-term inundation risks. SLOSH no longer meets today's higher accuracy demands for planning purposes. Comprehensive models such as ADCIRC and Delft3D, when coupled with a wave model and applied in high resolution, have proven to perform well for planning applications; for example, Westerink et al. [88] reported simulation error of 0.37 m, with respect to surge observations in coastal areas in the northern Gulf of Mexico.

Two primary methods have been developed to reduce the number of storms (i.e., samples) needed in surge simulations, while maintaining adequate sampling resolution and integration domain for representing the full JPM integral accurately: Surface Response Functions (SRF) ([33, 67, 68]; others) and Bayesian Quadrature [63, 80]. Both methods produce good results when compared to results using a larger number of samples; however, some assumptions initially developed for application in the central Gulf of Mexico are in need of additional review. One area of particular concern is the neglect of physical differences in storm characteristics in different parts of the world. For example, three physical factors are markedly different along the US East Coast compared to US Gulf Coast areas, which served as the development basin for the recent JPM approaches. First, tidal variations along the Gulf Coast are small compared to storm surges; whereas, along much of the US East Coast tidal variations

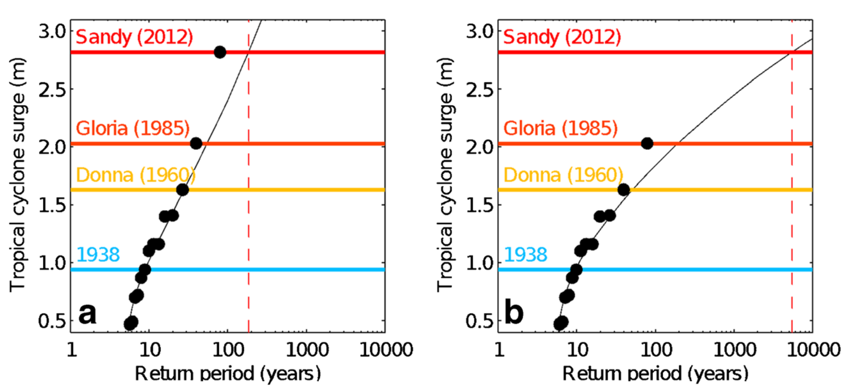

Fig. 2 Historical storm method (HSM; e.g., [77] as a recent example) with an assumed Generalize Extreme Value (GEV) distribution applied to observed surges (observed flood elevation minus predicted tide level) at The Battery in New York City (data from NOAA [2]). A peaks-over-threshold approach was applied using a 0.5-m surge threshold. **a** Results when the observational record from 1938 to 2012 is considered. This record includes 14 tropical cyclones, corresponding to an annual rate of occurrence of 0.19 events per year. **b** Results when the observational record from 1938 to 2011 is considered (excludes Hurricane Sandy in 2012). This record includes 13 tropical cyclones, corresponding to an annual rate of occurrence of 0.18 events per year

are of comparable magnitude to the surges. Second, many storms along the US East Coast are undergoing extratropical transition and have wind fields that deviate from the parametric forms adequately characterizing storms in the Gulf of Mexico [40, 71]. Third, the effect of more complex shoreline shapes (particularly in the New York Bight area) cannot be neglected in terms of its impact on storm track characteristics.

To minimize computational simulations in the central Gulf Coast region, tidal effects were added as a randomized linear superposition onto the modeled storm surges [63]. Whereas, this may be adequate in that region, larger tidal ranges in other areas introduce sampling errors of the type described by Irish et al. [34]. Other assumptions, such as (1) a single generalized distribution for storm sizes exists along the entire US East Coast [83] and (2) an omnidirectional basis, which assumes storm heading and storm intensity are independent, provides an optimal estimate for the geographic sample size [80], are also somewhat speculative. In the case of the first of these assumptions, extratropical transitions increase substantially north of 30–35° latitude. Such transitions can dramatically affect storm size characteristics, as seen in the case of Hurricane Sandy. In the case of the second assumption, the existence of strong correlations between storm intensity and the direction of storm heading would indicate that this assumption may not be justified in some areas, such as the New York Bight. Figure 3 shows a pronounced correlation between storm heading and lowest central pressures at closest approach

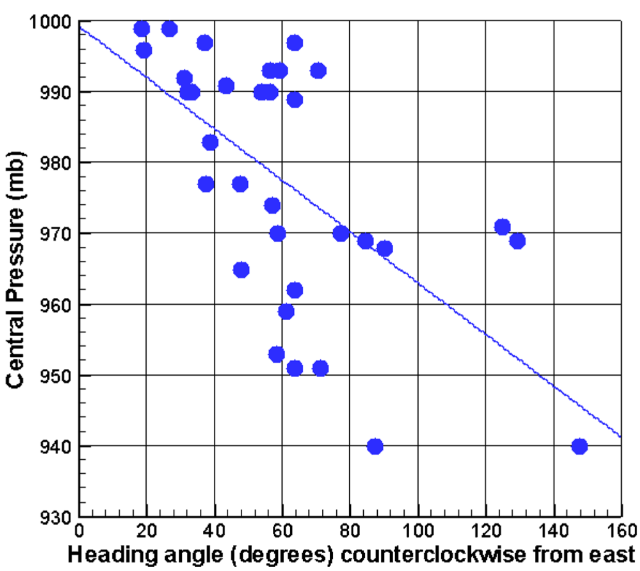

Fig. 3 Variation of lowest central pressure in an area defined in a region bounded by latitudes from 36.5° to 41° North and longitudes between 78-(0.222x[Latitude-36.5]) and 73-(0.222x[Latitude-36.5]) East based on the latest available HURDAT reanalysis [48, 50] using all data from 1930 through 2012. This defines the pressure characteristics in a region approximately the same width along the US East Coast from off the southern part of the Chesapeake Bay to the eastern part of Long Island plotted as a function of storm heading at the time of lowest pressure. The correlation is significant at the 0.01 level of significance. The angles here are heading directions measured counterclockwise from east

to landfall for an area along the US East Coast. The null hypothesis of independence can be rejected at a 0.01 level of significance, with storms approaching from land being weaker than those approaching from the open ocean. This implies significant under-prediction of the hurricane threat in the New York Bight area. This type of error in omnidirectional extreme analysis compared to directional analyses has previously been noted in studies by [16, 39]. The existence of localized effects such as these suggests that models developed and tested on a basin-wide scale, such as typically used to downscale tropical cyclone characteristics from circulation models, need to be carefully validated on a local basis before they are applied to a specific area.

Nonstationary Considerations—Decadal Variability and Long-Term Anthropogenic Climate Change

Thus far, we have considered challenges with current surge hazard assessment methods as they relate to representing the tropical cyclone parent population. However, long-term storm surge hazard is also potentially influenced by both climate variability and long-term climate change. Traditional extreme-value statistic approaches assume that storm surge is a stationary process, governed by a homogeneous compound distribution of a GEV-Poisson or GPD-Poisson type [54, 80]; however, in these studies and in all applications of the JPM-OS to date, the Poisson frequency is assumed to be independent from the intensity distribution. It is well-known that tropical cyclone frequency and intensity vary at the decadal and multi-decadal scale in response to cyclical, global phenomena such as El Niño-Southern Oscillation (ENSO) (e.g., [12, 21]). For example, Jin et al. [37] showed El Niño intensifies eastern North Pacific cyclones while Fitchett and Grab [19] showed strong interannual variability in cyclone landfall in southeast Africa. Colbert and Soden [8] and [65], respectively, showed ENSO and the Atlantic Meridional Mode impact cyclone track and intensity, largely explaining the temporal clustering of land-falling hurricanes in the US along the northeast Atlantic coast in the 1950s, along the mid-Atlantic coast in the 1990s, and along the northern Gulf of Mexico coast in the 2000s. As a simple example of the magnitude of this influence on extreme central pressures in the northern Gulf of Mexico, a sample of 5-year intervals from 1943 to 2012 HURDAT [49, 51, 52] was partitioned into two samples, one in which four or more storms originated or passed into an area anywhere north of 28° latitude during a 5-year interval and one in which less than this number occurred. The estimated 100-year central pressure was 924 mb for the case with lower storm numbers and 890 mb for the case of higher storm numbers. Clearly, the assumption of independence between storm frequency and storm intensity is not supported in this region.

The impact of climate variability on long-term storm surge hazard statistics is not yet fully quantified, but preliminary studies indicate that uncertainty introduced by climate variability into the probabilistic estimate is small with respect to other factors, so long as the trend is periodic and the record length for analysis captures this periodicity [34]. It is plausible, however, that this uncertainty may be significant in areas where these decadal and multi-decadal signals are more complex. Further, its impact on long-term hazard assessment may be significant.

The tropical cyclone surge hazard is potentially influenced by long-term, anthropogenic greenhouse-gas-driven climate change in two ways: (1) a mean increase in sea level (i.e., sea-level rise) upon which storm surge is generated and (2) a change in storm intensity and frequency. Both processes potentially increase the expected magnitude of the flood hazard as well as the uncertainty associated with projecting the hazard, yet changes in tropical cyclone intensity and frequency are also spatially variable. For example, Kossin et al. [47] showed a poleward migration of maximum cyclone intensity over the last 30 years, on the order of 50–60 km/decade. While global occurrence of tropical cyclones is expected to decrease in the future—modeling studies yield decreases in frequency in the range of 6 to 34 % globally by 2100 [44]—there is a wide variation in regional cyclone frequency projections (e.g., [4, 45, 84, 85]). For example, Emanuel [14] reported projections for the twenty-first century with a dramatic rise in tropical cyclone frequency in the western North Pacific with less activity in the southwestern Pacific. Projecting future tropical cyclone frequency remains an evolving research topic. On the other hand, there is community consensus that future cyclones will likely be more intense (e.g., [13, 15, 43, 87]). Knutson et al. [44] reported that projections using theory and dynamical models yield a 3 to 21 % global increase in tropical cyclone central pressure differential during the twenty-first century, where more recent studies continue to be consistent with these projections (e.g., [43]). Long-term shifts in storm track and changes in storm size are also critically important for understanding future surge hazard, and the impact of global warming on these parameters requires further study.

Future anthropogenic-induced changes in tropical cyclone frequency and intensity will change the surge hazard. To understand the magnitude of impact of cyclone intensification on the surge hazard, we consider the simple model of Knutson and Tuleya [46], where tropical cyclone wind intensity increases by approximately 4 % for every 1 °C increase in sea-surface temperature, and the momentum conservation argument for surge generation, where surge at a given location is proportional to wind speed squared. It thus follows that surge will increase on the order of 8 % for every 1 °C of sea-surface temperature warming [89]. This means that areas more susceptible to significant wind surge generation, namely those areas that are low-lying and are exposed to intense storms, will exhibit a relatively larger increase in surge hazard. A temperature rise of 1 to 5 °C over the next century (e.g., [74]) translates to an approximate increase in storm surge hazard of 8 to 40 %, for example, a 2.0-m surge (on the order of the 100-year event in New York City; [53]) increases by 0.2 to 0.8 m while a 5.0-m surge (on the order of the 100-year event in greater New Orleans, Louisiana; [63]) increases by 0.4 to 2.0 m.

The impact of frequency change on the surge hazard may be approximated directly in terms of the return period, T: $T_{\text{future}}=T_{\text{present}}/(1+\alpha)$, where α is the fractional change in cyclone frequency. Considering the range of frequency projections over the next century, from a global decrease on the order of 40 % [44] to a global increase on the order of 40 % ([14], when a very high greenhouse gas concentration is considered), the 100-year return period (0.010 annual exceedance probability, AEP) changes to 170 (0.006) to 70 (0.014) years (AEP). The quantitative impact on surge elevation, however, will be site specific and will depend on the shape of the extreme probability distribution. For example, Lin et al.'s [53] present-day estimate for New York City varies from approximately 1.5 to 2.0 m over the 70- to 170-year return periods. Similarly, Niedoroda et al.'s [63] present-day estimate for greater New Orleans varies from approximately 4.3 to 5.1 m over the 70- to 170-year return periods. At both locations, the impact of frequency change over the next century on surge hazard is similar and is no more than 0.4 m at the 100-year return period. In other locations, the impact of frequency change could be larger, but we anticipate this influence will not change statistical surge height by more than 0.5 m. For practical application at this time, these tropical cyclone intensity and frequency trends may be best quantified via added uncertainty in the surge hazard analysis [66] and reassessed periodically as part of an adaptive management strategy [32].

While the impact of future changes in tropical cyclone intensity and frequency on future coastal flooding may be important in many local areas, it is expected to be less significant than the impact of future sea-level rise, especially in areas characterized by low-lying sedimentary coastlines ([89] and references therein). Considering only a static rise in mean sea level, total depth across the full range of return periods are likely to increase on the order of 1 m by the end of this century (e.g., [64]). For example, Lin et al. [53] considered both projected future tropical cyclone ensembles and static increases in baseline mean sea level to project the future flood hazard in New York City. Despite the above-mentioned concerns regarding the omission of dependency between track angle and cyclone intensity in this analysis, Lin et al.'s projections over a large range of extreme-value probabilities showed the dominating contributor to the accelerating flood hazard is sea-level rise (exhibiting an increase in flood level on the order of 1 m under 1 m of sea-level rise), with impacts from future changes in tropical cyclone climatology playing a secondary role. Yet, projections of global sea levels over the twenty-first century carry great uncertainty, with projections ranging from 0.2 to 2 m (e.g., [61, 81] and references therein; [64] and references therein), where the latest Intergovernmental Panel on Climate Change reporting a modest range of 0.26 to 0.82 m ([74] and references therein), with significant additional contributions to local sea-level rise in many locations, for example, due to sediment compaction or tectonics. Despite this uncertainty in the future rate of sea-level rise, that there will be future sea-level rise is certain and its magnitude is expected to be significant enough to be the dominating contributor to future changes in the surge hazard.

Sea-level rise not only raises the mean sea level upon which surge is generated and propagates, but also facilitates long-term changes to the coastal landscape, potentially resulting in changes in underlying tidal dynamics (e.g., [22]) and enabling larger surges to propagate farther inland (e.g., [5, 35]). For example, barrier island degradation induced by sea-level rise reduces the ability of these natural features to prevent ocean surge and waves from entering back-barrier areas [31]. Likewise, sea-level rise induced changes to natural ecosystems, such as wetlands, and alters surge and wind wave generation and propagation (e.g., [18, 30]). But, these processes are highly nonlinear, for example, Loder et al. [55] showed decreased resistance arising from wetland degradation (facilitating surge propagation) may be offset by increased water depths created as wetlands erode (inhibiting surge generation). Studies to assess the future surge hazard have to date largely ignored these dynamic shoreline and land cover dynamics, largely due to the difficulty and uncertainty in predicting and modeling these future changes. Rather, regardless of statistical approach most studies considered only the direct influence of an increase in baseline mean sea level (e.g., [32, 53, 77]), and thus miss the potentially critical role of sea-level rise induced landscape changes on tropical cyclone flooding. While the quantitative impact of these landscape changes on the future surge hazard are not well understood, preliminary research suggests degradation of barrier islands and wetlands double the rise in flood elevation, with respect to static sea-level rise on its own, in some locations [31, 35]. Further study is needed to fully understand the significance of sea-level rise induced landscape changes on the surge hazard.

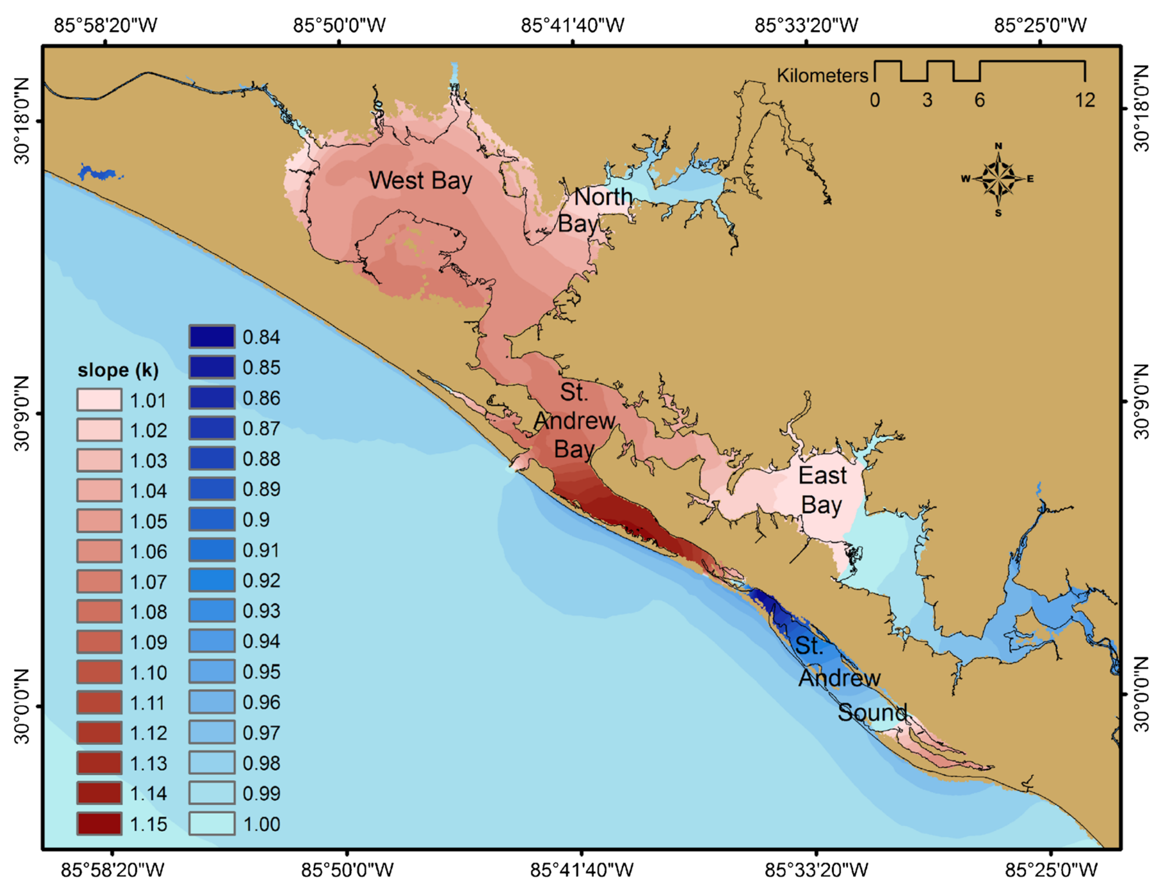

Fig. 4 Tropical cyclone flood elevation bias induced by nonlinearities in surge generation and sea-level rise at Panama City, FL. The relationship between dynamically simulated future flood elevation (z_{SLR}) and the summation of present-day surge (ζ) and sea-level rise (SLR) follows the linear form $z_{SLR}=k(\zeta+\mathrm{SLR})+a$, where slope k and a are location-specific constants. Here, a is small such that slope k (shown here) represents one plus the fractional change in z_{SLR} with respect to (ζ+SLR). From Taylor et al. [76]

Furthermore, many hazard and risk assessment studies approximate the impact of sea-level rise on future tropical cyclone flooding statistics via direct linear summation of the present-day probabilistic hazard assessment and projected sea-level rise (e.g., [57, 72, 75, 77]), ignoring nonlinear interactions characteristic of complex coastlines and estuarine environments (e.g., [91, 93]). This is problematic because this approach potentially creates a bias, on the order of 15 % in the future flood elevation (Fig. 4), either high or low depending on exact geographic location (e.g., [76]).

Implications on Future Tropical Cyclone Risk Assessment

To this point, we focused discussion on quantification of tropical cyclone surge hazards. Yet, risk assessment requires integration of the likelihood of hazards occurring with potential consequences (impacts) when they occur. Potential consequences include loss of life, injury, direct and indirect economic damage, immediate and long-term social impacts, and ecosystem damage, among others. Largely due to the relative ease of analysis, with respect to quantification of other consequences, the majority of literature on tropical cyclone risk assessment considers economic damage or population affected as the primary impact (e.g., [17, 23, 62, 86]), using risk measures such as annualized economic damage (e.g., [38]). It should be recognized, however, this is only one measure of risk and does not fully represent the range of consequences to society and the environment. A particular challenge is that we currently lack methods to systematically and quantitatively integrate intangible impacts to, for example, the community and individual wellbeing.

Projecting future risk requires knowledge of changes in expected physical surge hazards as well as changes and expected evolution of coastal landforms, socioeconomic status, infrastructure vulnerability, and ecological health. Recent studies considering future population and economic growth, climate change, and HSM-based flood probabilities in port cities worldwide suggest urban centers in the western North Atlantic, western North Pacific, and northern Indian Oceans are most vulnerable to impacts from future tropical cyclone flooding (e.g., [23, 24])—including the cities of Calcutta, Dhaka, Shanghai, Houston, Miami, New York, Tokyo, and Hong Kong. Yet, comprehensive quantification of future tropical cyclone risk should consider the following:

1. The complete hydrodynamic loading at the coast, inclusive of wind waves (e.g., [79]) and currents.
2. Integration with other damaging processes such as wind (e.g., [7];) and precipitation flooding (e.g., [3]).
3. Post-disaster socioeconomic (e.g., [36, 70]) and ecological recovery ([6]).

The last of these necessitates an understanding of the plausible sequencing and magnitude of tropical cyclone surge events, as well as an understanding of the amount of time a community or ecological system, requires to recover from a disaster of some specified magnitude, i.e., community or ecological resilience. Such quantification must consider a combination of probabilistic and deterministic tropical cyclone characteristics, for example, by considering decadal trends in cyclone frequency and tracks and their related dependence on intensity. Additionally, to fully capture the range and uncertainty in such future risk projections, a range of future climate and sea level, resulting landscape changes, and resulting community resilience and adaptation projections must be considered.

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