Tropical cyclone climatology change greatly exacerbates US extreme rainfall-surge hazard

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Abstract

Tropical cyclones (TCs) are drivers of extreme rainfall and surge, but the current and future TC rainfall-surge joint hazard has not been well quantified. Using a physics-based approach to simulate TC rainfall and storm tides, we show drastic increases in their joint hazard from historical to future projected (SSP5 8.5) conditions. The frequency of joint extreme events (exceeding both hazards' historical 100-yr levels) may increase by 7-36 fold along the southern US and 30-195 fold in the northeast by 2100. This increase in joint hazard is induced by sea-level rise and TC climatology change; the relative contribution of TC climatology change is higher than that of sea-level rise for 96% of the coast, largely due to rainfall increases. Increasing storm intensity and decreasing translation speed are the main TC change factors that cause higher rainfall and storm tides and up to 25% increase in their dependence.

Coastlines across the globe are vulnerable to the joint occurrence of high sea levels and intense rainfall[1–3], which can increase flooding beyond the level predicted by considering either hazard alone and result in compound floods[4,5]. Coastal compound floods are most often triggered by cyclonic storm events, either tropical cyclones (TCs) or extra-tropical cyclones (ETCs)[3], which are both low pressure systems that can generate significant storm surges and rainfall[5]. The future incidence of coastal rainfall and storm tides may be affected by the combination of sea-level rise (SLR) and changes in storm climatology. Recent projections of storm climatology change suggest an increase in the probability of joint rainfall-surge events along much of the global coastline, mostly driven by an increase in rainfall hazard[6,7]. Previous studies of US compound flood potential have considered changes in the joint hazard resulting from changes in a subset of climate-induced variables, such as SLR[8] and changes in river flow[9] or rainfall[10].

Along the US Atlantic and Gulf Coasts, TCs are one of the largest drivers of coastal flood losses[11,12]. Although less frequent than ETCs at mid-high latitudes, TCs typically dominate the upper tail distribution (>50 year return period) of both storm surges[13,14] and rainfall-induced flooding[15,16], and TCs have been responsible for many extreme compound floods[1,17]. However, few regional studies of compound flood hazard have explicitly accounted for TC events[10], due to their sparse occurrence in the historical record and challenges in representing TCs within reanalysis datasets and typical global circulation models (GCMs)[7]. It is unclear how future changes in TC climatology and SLR will alter the severity and spatial variation of extreme rainfall-surge hazard across the US Atlantic and Gulf Coasts, what will be the relative contribution of storm climatology change and SLR to changes in the joint hazard, and how changes in TC characteristics are related to changes in rainfall hazard, storm surge hazard, and their dependence.

To address these questions, we apply a full probabilistic joint hazard analysis framework to investigate the current and future joint rainfall-surge hazard from TC events impacting the US Atlantic and Gulf Coasts under the combined influence of end-of-21st century high emission scenario SLR (RCP 8.5)[18] and storm climatology change (SSP5 8.5)[19]. We generate synthetic TCs from a statistical-deterministic TC model[20] forced with reanalysis or GCM output. 5018 synthetic TCs consistent with the historical (1980-2005) climate (equivalent to 1500 simulation years) are downscaled from NCEP reanalysis data and used to represent the historical storm climatology. 6200 projected future (2070-2100) TCs are downscaled from each of eight CMIP6[19] GCMs, bias-corrected, and combined into a single weighted-average composite projection (for 800 simulation years) that represents the future storm climatology (see Methods). We simulate storm tides (storm surge plus astronomical tide) for each event with the advanced circulation (ADCIRC) hydrodynamic model[21,22], using a high-resolution mesh that spans the entire North Atlantic basin and has been previously validated[23] (Methods). We estimate rainfall fields using the physics-based Tropical Cyclone Rainfall (TCR) model, which has previously been used to assess historical rainfall climatology[24,25], project changes in rainfall hazard[26], and simulate flood impacts[27,28] (Methods). To evaluate the impact of SLR, we incorporate spatially-varying, probabilistic

SLR projections for 2100 from ref. [18], which are based on projections from a suite of CMIP5 GCMs (Methods).

To focus on a particular metric to measure the joint hazard, we define a joint extreme event as one that exceeds both the historical 100-year storm tide (relative to the historical sea level) and the historical 100-year 24-hour rainfall at a given coastal location. Based on the simulations and bivariate extreme value analysis, we quantify the return period of the joint extreme event (henceforth referred to as JRP) in the historical and future climates (see Methods) and show that SLR and TC climatology change cause drastic increases in the frequency of joint extreme events. We quantify the relative importance of the change of different climatological variables (i.e., sea level, storm frequency, rainfall, storm tides, and hazard dependence) in driving the changes in JRP (Methods) and find that TC climatology changes drive larger increases in the joint hazard compared to SLR. We further investigate the effect of TC characteristic changes and find that increases in intensity and decreases in translation speed cause increases in rainfall and surge hazards as well as their dependence. Our findings motivate explicit consideration of TC climatology changes in compound flood hazard analysis.

Spatial pattern of current and future joint hazard

For each location along the coastline, we calculate the peak storm tide and maximum 24-hour rainfall accumulation occurring anywhere in the upstream catchment for each storm event. Based on the NCEP simulations, we quantify the univariate 100-year storm tide (i.e., the storm tide level that has a 1% annual probability to be exceeded) and univariate 100-year 24-hour rainfall for the historical period (Fig. S1). Using the thresholds of historical 100-year storm tide and rainfall, we quantify the probability of joint extreme event occurrence through JRP in the historical climate (Fig. 1a) and in the future climate (Fig. 1b). We also show the most dominant driver of the JRP change in Fig. 1c. There are large variations in JRP across the US coastline under historical conditions (Fig 1a). The coastlines of the Gulf of Mexico and Southeast Atlantic (up to Chesapeake Bay) have lower JRP, typically ranging from 200-500 years, signifying a higher probability of joint extreme occurrence compared to other regions. JRP increases along the northern Mid-Atlantic (up to Connecticut) due to a decrease in the statistical dependence between storm tide and rainfall. Along the New England coastline JRP is much larger than other regions (>1000 years) because in this region the two hazards occur almost independently. The low correlation between rainfall and storm tides in New England is due to the large tidal constituents that dominate total extreme sea levels compared to TC-induced storm surges[23].

Due to the combination of future storm climatology change and SLR, future JRP may decrease to 3-30 years, with higher JRP values along the Gulf of Mexico and Southeast Atlantic (10-30 years) and lower JRP along the Mid-Atlantic and New England region (3-10 years; Fig. 1b). The reason for higher future JRP along the southern coastline is because these regions are already prone to extreme rainfall and surges in the historical climate (Fig S1) and the percent increase in the hazard there is smaller than the percent increase for northern regions. Thus, across the entire coastline, JRP decreases drastically compared to its historical values. Also, the change in JRP generally increases moving from south to north, with the largest decreases in JRP occurring in northern locations. However, even the locations of smallest JRP change still correspond to a 7-fold increase in the frequency of joint events. The southeast Florida coast (i.e., Miami region) is an exception to the spatial trend of future JRP. Here, the historical JRP is 600 years and the future JRP is 3 years, resulting in a JRP change that is much greater than the JRP change for the rest of the Southeast Atlantic. The reason for the large change in JRP in the Miami region is because modeled extreme storm tides and TC rainfall are not highly correlated in the historical period, but large increases in rainfall hazard and SLR in the future cause the joint extreme sea level and rainfall thresholds to be exceeded frequently.

The projection of JRP is associated with statistical and physical modeling uncertainties; Figure 2 depicts the median JRP estimate (as discussed above) and 95% boot-strapped sampling uncertainty bounds under historical (gray) and composite future (blue) conditions and the JRP estimates from individual GCMs for representative coastal locations. The sampling uncertainty ranges of the composite future JRP (blue boxes) are much smaller than the historical uncertainties, since joint exceedances are more frequent in the future period and consequently JRP can be estimated with less sampling uncertainty. The variations in JRP estimates among different models are primarily due to differences in the future projected TC frequency and intensity. MPI, MRI, and GFDL consistently predict smaller decreases in JRP since these GCMs project low/no increase in storm frequency (Fig S2) and low-moderate increases in storm intensity (Fig S3). Conversely, ECEARTH and IPSL consistently predict large decreases in JRP since both models project the highest increases in storm frequency and intensity. The variations among the GCMs are consistent for the entire coastline (Fig. S4). Although there is a relatively large inter-model range of future JRP estimates, especially for locations in the Gulf of Mexico, even the most conservative GCM (i.e., MPI) projects large increases in future joint hazard.

Drivers of joint hazard change

The change in JRP can be driven by three mechanisms: 1) changes in storm frequency, 2) marginal changes in rainfall totals and/or extreme sea level driven by TC climatology changes and SLR, and 3) changes in the statistical dependence between extreme rainfall and storm surges. To understand the relative contribution to changes in JRP from each mechanism, we calculate the isolated impact of changes in storm frequency, rainfall hazard, storm tide hazard, hazard dependence, and SLR (see Methods). In Figure 1c we plot the single variable that causes the largest decrease in JRP at each coastal location. Across the Gulf of Mexico and Florida coastline, the increase in rainfall is the largest driver of changes in JRP, while the increase in storm frequency has the largest impact on JRP change for parts of the Southeast and Mid-Atlantic. Along the upper Mid-Atlantic and New England coastline, SLR causes the largest decrease in future JRP. For the select locations, we show the relative impact on JRP change of each variable and the combined impact of all storm climatology variables (Fig 3). Across all locations in Fig 3 the change in marginal rainfall distribution is among the largest contributor to the change in JRP, since all GCMs project significant increases in rainfall totals (Fig S5) due to both the increased saturation specific humidity of the warmed environment and the projected increase in TC intensity. In contrast to the large rainfall impact, the change in marginal storm tide distribution has small impact on the change in JRP for northern locations and a small to moderate impact on JRP change for locations along the Gulf of Mexico. The relative impact of SLR on JRP change generally increases moving south to north, with the largest impact at Portland, ME. Importantly, the storm climatology changes drive large increases in joint hazard across all locations. The combined impact of storm climatology changes on JRP is larger than the SLR impact for 96% of locations along the coastline.

The change in the dependence between hazards also causes a small to moderate decrease in JRP for most locations in Figure 3, indicating that the extremes of the two hazards are projected to become more dependent in the future climate. To further examine the change in hazard dependence, Figure 4a shows the conditional probability of 24-hour rainfall exceeding the 90th percentile given a storm tide that exceeds the 90th percentile, calculated for the historical period. The conditional probability is a representation of the tail dependence between the hazards, as higher conditional probability corresponds to higher tail dependence. The eastern Gulf of Mexico and Chesapeake Bay exhibit the strongest dependence between hazards, the western Gulf of Mexico and Southeast Atlantic have moderate hazard dependence, and the Mid-Atlantic and New England have relatively low dependence. Figure 4b shows the change in the conditional probability from the historical to future climate, with areas of red (blue) indicating statistically significant increases (decreases) in dependence. With the exception of the eastern Gulf of Mexico, Chesapeake Bay and the Maine coastline, most regions are projected to have higher dependence between extreme rainfall and storm tides in the future. Specifically, the lower Texas, Georgia, North Carolina, and New Jersey coastlines are projected to experience the largest strengthening of hazard dependence in the future, resulting in up to an increase of 0.2 in the conditional probability (Fig. 4b). Along the eastern Gulf of Mexico there is almost no change in the dependence strength because the two hazards are already highly correlated in the historical climate (Fig 4a) and will remain similarly correlated in the future climate. Along the coast of Maine there is a small projected increase in hazard dependence, although this increase is not statistically significant. The Chesapeake Bay stands as an outlier, and it is the only location where the dependence strength between hazards decreases in the future climate (discussed below).

Changes in dominant TC storm characteristics

Since TC climatology change is the dominant contributor to JRP change, we investigate how projected changes in TC storm characteristics drive changes in rainfall accumulations, peak storm surges, and their dependence at the coast. After investigating correlations between each hazard and storm intensity, approach angle, translation speed, and landfall location and quantifying projected changes in each storm characteristic, we find that storm intensity and translation speed are both projected to change significantly in the future (Fig 5a and 5b, respectively) and are significantly correlated with rainfall and/or storm tide (Fig 5c-f). For the vast majority of the coastline, both the peak storm tide and 24-hour rainfall are significantly correlated with TC intensity, although the strength of correlation is higher for rainfall (Fig 5c-d). The 24-hour rainfall is also strongly negatively correlated with storm translation speed (Fig 5f), as slower moving storms will drop more rainfall in a given coastal location than faster moving storms. The peak storm tide is not strongly correlated with translation speed (Fig 5e), since both slow and fast moving storms can generate high surges, and the additional background wind contribution is generally small, even for fast moving storms, compared to the cyclonic wind speed. Under future storm climatology, the 90th percentile of TC intensity is projected to increase by 15-30% along the Gulf of Mexico and Southeast Atlantic, 30-50% along the Mid-Atlantic, and 20-30% along the New England coastline (Fig 5a). The vast majority of previous studies also project an increase in North Atlantic TC intensity, and many predict an increase in the frequency of high intensity (category 3-5) TCs[29]. We also find a large future reduction in the translation speed of storms that exceed the 90th percentile intensity (Fig 5b). For all regions except New England, storms that exceed 90th percentile intensity are likely to move 20-30% slower in the future than in the historical period. The decrease in translation speed found here is consistent with previous work examining changes in translation speed in the historical record[30] and projections of TC translation speed under future climate conditions[31–33]. The increase in storm intensity coupled with the decrease in translation speed drives an increased likelihood to observe both extreme rainfall and extreme storm tide in the future and increases the upper tail dependence between the hazards. By comparing Figure 4b with Figures 5a-b it is clear that most regions experiencing a significant increase in the hazard dependence also experience significant increases in storm intensity and decreases in translation speed. The Chesapeake Bay is a notable exception, since the hazards are projected to become less dependent in the future even though there is an increase in TC intensity and decrease in translation speed. In the future a larger number of intense storms are projected to approach the coast north of the Bay opening. These storms do not induce high storm surges within the Bay since the cyclonic winds are pointed away from the coast, but they still induce extreme rainfall. Thus, the increase in the number of these types of storms causes a decrease in the hazard correlation at this location in the future climate.

Discussion

The results presented here demonstrate that TC climatology change and SLR may cause large increases in joint rainfall-surge hazard across the US East and Gulf coasts. The projected increase in extreme rainfall hazard (considering the maximum 24-hour rainfall accumulation over the catchment in the above analysis) is often the largest driver of the increase in the extreme joint hazard. Our projections of extreme rainfall are consistent with refs. [26] and [34], who found 100-120% increase in the 100-year storm total rainfall at a single point location in Houston, TX, while we project a 123% increase (Table S2). Our projections are also consistent with previous studies focusing on mean rainfall changes. Using the RCP 4.5 scenario and a suite of CMIP5 models, most previous studies found a 10-22% increase in mean end-of-century TC rain rates within 100 km of the storm center[35–37]. A recent study using a high-resolution GCM projected a larger increase of 29%[38]. Here we project a slightly higher 32% increase in inner core mean TC rain rate (Table S1), which is reasonable given our use of the SSP5 8.5 high emission scenario.

We also find that the overall impact of storm climatology change on the change in the extreme joint hazard is larger than the SLR impact for 96% of the coastline. The contribution of TC climatology change is also dominant for lower joint TC hazard thresholds, such as 25-year or 50-year levels (see Table S3; Fig. S6). Although we find that TC climatology change is more dominant than SLR in driving changes in TC joint hazard, SLR also impacts other types of compound flooding arising from e.g., ETCs or two unrelated meteorological events, especially for return periods shorter than 50 years[13–16]. Moreover, recent work in ref. [39] that incorporated a physical model for ice sheet hydro-fracturing, a mechanism that is deeply uncertain, found significantly higher SLR by 2100 than ref. [18] (which we use here). Therefore, the overall role of SLR on total compound flood hazard may still be dominant compared to TC climatology change.

The findings presented here are associated with inevitable uncertainties. We utilize a single TC model to downscale all GCMs and reanalysis data, and the model predicts a significant increase in future TC frequency for five of the eight GCMs. Although a few other studies[40,41] have also predicted increases in TC frequency, the majority of studies predict a decrease or no change in North Atlantic storm frequency[29]. However, the main findings of our study are unchanged even if we assume no change in future TC frequency. The future JRP change calculated by holding TC frequency constant at the historical level is only slightly lower at each coastal location (up to 149-fold decrease in JRP; see comparison in Fig S7), and the spatial trends (i.e. higher JRP change in the north compared to the south) are unchanged. The relative importance of TC climatology change compared to SLR also remains similar when assuming constant frequency, and TC climatology change still causes a larger JRP change than SLR for 84% of the coastline. The reason our results are relatively unchanged if we neglect the projected frequency change is because the increase in TC hazards and their joint occurrence is largely driven by projected increases in TC intensity and decreases in translation speed.

This study cannot directly predict the overall compound flood hazard, which is driven by a combination of ETC events (especially at lower return periods) and TCs. Moreover, compound flood depths must be quantified using high-resolution inundation models. Nevertheless, we provide evidence that joint rainfall-surge extreme events could become an increasing threat to coastal communities in the future. We also find that the statistical dependence between extreme rainfall and storm tide increases in the future for portions of the coastline, resulting in a higher probability of multi-hazard extremes during future storm events. This finding is significant since many previous studies of future compound flooding have neglected potential increases in hazard dependence[8–10,42], which could underestimate compound flood risk. Our projections of joint TC rainfall-surge hazard can be combined with ETC hazard distributions[43] to develop overall flood mapping scenarios[44] for regional[10,45] or local-scale[17,46,47] flood models to assess the impact of joint rainfall-surge occurrence on coastal flooding in a changing climate.

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Author Contributions

A.G. and N.L designed the study and N.L supervised the modeling and analysis. A.G. performed the hydrodynamic modeling and statistical analysis. A.G. and D.X. performed the rainfall modeling. K.E. modeled the synthetic tropical cyclones. All authors contributed to writing and editing the manuscript.

Competing Interests

The authors declare no competing interests.

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Figure Captions

Figure 1: Joint rainfall-surge hazard in the current and future period and largest driver of joint hazard change. Joint return period of NCEP historical 100-yr rainfall and 100-yr sea level (JRP) for (a) NCEP historical period and (b) future period (2070-2100) based on GCM composite projection and 2100 SLR. Black dots in (a) show representative locations that are analyzed further in Figures 2-3. Red tick marks in (a) show boundaries of Gulf of Mexico, Southeast Atlantic, Mid-Atlantic, and New England. (c) Largest single factor contributing to increase in joint hazard or N/A if no single hazard is larger than others. US state outlines come from the U.S. Census Bureau[48].

Figure 2: JRP sampling uncertainty and model ranges for representative coastal locations. JRP estimates and 95% boot-strapped uncertainty bounds under NCEP historical (gray) and GCM future composite (blue) forcing. GCM model ensemble spread at each location for the future period (2070-2100) shown as colored dots.

Figure 3: Relative impact of each single climate factor on JRP change and impact of total changes in TC climatology or sea level rise. Zero indicates no change in JRP compared to NCEP historical JRP and one indicates that the factor causes the entire change between

historical and future JRP. Negative impact values indicate that the factor increases the JRP compared to historical best estimate (vertical black lines in Fig 2a). Note that the combined impact of all climate factors on JRP is highly non-linear and thus the sum of the relative impact of each single factor does not equal one.

Figure 4: Historical and future change in tail dependence between 24-hour rainfall and peak storm tide. (a) Conditional probability of extreme rainfall (exceeding 90th percentile) given extreme storm tide (exceeding 90th percentile) in the historical period, and (b) change in conditional probability of extreme rainfall due to future storm climatology. Positive (negative) values indicate increases (decreases) in conditional probability. Areas of gray indicate that the projected change in conditional probability is not significant compared to the range of natural variability in the historical period (set as the 10-90 percentiles of the tail dependence estimated through bootstrapping). US state outlines come from the U.S. Census Bureau[48].

Figure 5: Change between future composite TC characteristics and historical characteristics and correlation between rainfall/storm tide and TC characteristics. Change in (a) 90th percentile TC intensity (Vmax), and (b) median translation speed (Vt) of storms that exceed 90th percentile intensity. Kendall correlation between Vmax and storm tide (c) or rainfall (d) and between Vt and storm tide (e) or rainfall (f). US state outlines come from the U.S. Census Bureau[48].

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Methods

To characterize the present and future joint rainfall-surge hazard, we implement a physics-based modeling framework that is driven by the large-scale atmospheric and ocean climatology of reanalysis (historical period) or GCM (future period) data. First we construct monthly climatologies of relevant environmental variables (see ref. [48]) based on the reanalysis/GCM data. Next, we generate thousands of synthetic TCs that are consistent with the large-scale environment using a statistical-deterministic TC model. These synthetic TCs represent around 1000 simulation years for each climate condition. For each TC we model the coastal storm tides using a high-resolution hydrodynamic model, and we model the rainfall fields using a computationally-efficient physics-based rainfall model. Based on the modeled storm tides and rainfall accumulations for the thousands of synthetic TCs, we conduct bivariate statistical analysis to quantify the probability of joint extreme events.

Data

We generated 5018 synthetic TC tracks for the historical time period (between 1980 and 2005), based on the National Centers for Environmental Prediction (NCEP) reanalysis[49]. We then generated 4400 synthetic TCs for the historical period (1984-2005) and 6200 TCs for the future period (2070 to 2100) under the Shared Socioeconomic Pathway (SSP) 5, 8.5 emission scenario[50] based on each of eight CMIP6[50] climate models: Canadian Earth System Model (CANESM), Centre National de Recherches Météorologiques (CNRM), EC-Earth Consortium Model (ECEARTH), Geophysical Fluid Dynamics Laboratory Climate Model (GFDL), The Institute Pierre Simon Laplace Climate Model (IPSL), Model for Interdisciplinary Research on Climate (MIROC), Max Planck Institute Earth System Model (MPI), and Meteorological Research Institute Earth System Model (MRI).

Synthetic TC Model

The statistical-deterministic TC model[51], which has been widely applied for TC hazard assessment[52-56], generates synthetic events based on data about the large-scale environment and can be forced with either reanalysis data or projections from GCMs. Vortices are randomly seeded in space and time, and are moved according to the large-scale environmental winds plus a beta-drift correction[57]. TC intensity is estimated at each time step based on the Coupled Hurricane Intensity Prediction System (CHIPS), which is an axisymmetric vortex model coupled to a 1D ocean model[58]. Storms are only retained if their intensity exceeds 21 m/s (40 kts). Thus, only seed vortices that encounter favorable large-scale environment conditions will strengthen into TCs, and the timing of TC development is consistent with the environmental climatology. For each TC, the outer radius at which the cyclonic wind speed goes to zero (henceforth outer radius) is randomly drawn from an empirical lognormal distribution[59]. We neglect the variation in outer radius size over the TC lifetime[60] since previous work has shown the outer radius variation to be relatively small[61]. We also assume no change in the distribution of TC outer size for the future climate since historical trend analysis for the North Atlantic basin found no statistically significant changes in TC size over time[62]. Moreover, an analysis of dynamically-downscaled TCs based on RCP 4.5 end of century forcing found nearly constant outer radius compared to the historical period[63]. Using the CHIPS-estimated intensity and outer radius, we estimate the radius to maximum winds based on a theoretical wind model that links the outer descending region of the TC with the inner ascending region[61]. Each simulated storm is characterized by time series of storm parameters (time, center position, maximum wind speed, pressure deficit and radius to maximum wind) for every two hours.

Bias Correction and Model Combination

The downscaled TCs from each GCM may be biased compared to the NCEP-downscaled TCs, and biases within the TC characteristics can propagate to become biases in the hazard estimation. TC intensity and annual frequency are both important drivers of coastal flood risk, and both variables may be biased due to biases in GCM projections. Therefore, we perform bias correction at the storm level based on the differences between the NCEP TC frequency and intensity distribution and the GCM-predicted frequency and intensity distribution for the historical period. Using our method of bias correction, we avoid multivariate bias correction on the modeled storm tides and rainfall, which often fails to preserve the entire dependence structure between hazards[64]. Additionally, bias correction at the storm level is computationally efficient, while bias correction at the hazard level requires performing intensive hydrodynamic simulations for additional thousands of GCM TCs for the historical period.

Specifically, at each location we bias correct the TC frequency by multiplying the GCM-predicted future frequency by the ratio of the NCEP-derived historical frequency and GCM-predicted historical frequency.. To correct the GCM-projected TC intensity (Vmax) of each storm set, we first utilize the quantile delta mapping approach described in ref. [65] applied to each location along the coast. Essentially, the change between the GCM-projected future (2070-2100) and historical (1984-2005) downscaled Vmax quantiles is added to the NCEP-downscaled historical quantiles to create a corrected future Vmax distribution for each GCM model at each location. Then by the principle of importance sampling[66] the GCM-projected storms are weighted and re-sampled with weights corresponding to the ratio of the corrected Vmax probability density to the GCM-projected Vmax probability density. By doing weighted re-sampling of the storms at each location we are able to match the corrected future Vmax distribution and consequently generate a storm set at each location that is unbiased with respect to the intensity distribution. Figure S8 shows the bias correction procedure applied at a sample location for a sample GCM, demonstrating that after weighting/re-sampling the target Vmax distribution is matched accurately. We also create a composite projection for the future climate using a weighted average across all GCM storm sets, where the weights of each GCM are based on their Willmott skill[67] in matching the NCEP TC intensity return level curve in the historical period (Fig. S9).

Hydrodynamic Modeling

We simulate TC storm tides using the 2D depth-integrated version of the ADvanced CIRCulation (ADCIRC) model[68,69]. We utilize an unstructured computational mesh developed by ref. [70] that spans the entire North Atlantic basin and has resolution varying from >50 km in the deep ocean to ~1 km near the coastline. Eight tidal constituents are incorporated as periodic boundary conditions at the ocean boundaries of the mesh, and tidal data are obtained from the global model of ocean tides TPXO8-ATLAS[71]. The timing of the tide is matched to the timing of the synthetic storm (simulated according to the climatology). Wind and pressure fields are developed based on the Vmax and radius to maximum wind (Rmax) of each synthetic TC and physics-based parametric models[72,73]. Further details regarding the mesh formulation, tidal forcing, and wind/pressure models are documented in ref. [70]. Simulated storm tides from the model configuration utilized in this study were compared against observed water levels for 191 historical TCs impacting the US East and Gulf Coasts, and the model was found to satisfactorily reproduce peak storm tides (with an average root mean square error of 0.31 m and Willmott skill[67] of 0.90)[70]. In this study we do not account for wave setup since the computational expense of coupled wave-surge model would prevent a large-scale Monte Carlo risk assessment. For each TC we extract peak storm tides at nodes along the coastline that are spaced roughly 25 km apart.

Rainfall Modeling

We estimate rainfall fields from each synthetic TC using the Tropical Cyclone Rainfall (TCR) model described in refs [74]. TCR is a physics-based model that simulates convective TC rainfall by relating the precipitation rate to the total upward velocity within the TC vortex. Vertical velocity is estimated by taking into account frictional convergence, topographic forcing, vortex stretching, baroclinic effects, and radiative cooling. TCR has been previously utilized in risk assessment studies[55,75] and was recently compared against observed TC rainfall across the US[56,76]. It was found in ref. [76] that TCR simulates the rainfall climatology of coastal regions with relatively good accuracy, although it underperforms in inland and mountainous regions. The performance of the model for inland regions has been addressed and improved in subsequent work leading to ref. [56]. TCR does not simulate outer TC rain bands, which are three-dimensional in nature and cannot be directly simulated with an axisymmetric model. Nevertheless, a recent study modeled compound flooding using TCR-predicted rainfall fields for several historical events and found that TCR rainfall produced similar flood depth/extent compared to using radar rainfall forcing[55]. In our study, we utilize TCR rainfall over each coastal catchment delineated according to USGS hydrologic units (HUs)[77]. We pair each coastline point with its upstream coastal catchment, and for the coastal point we utilize the maximum 24-hour rainfall accumulation occurring anywhere in the upstream catchment as our rainfall metric for each storm event. The 24-hour storm duration is frequently used for rainfall risk assessment studies[78], and rainfall occurring anywhere in the immediate upstream catchment will drain to the same coastal point and can impact compound hazard.

Validation of integrated modeling of TC surge-rainfall hazard

Previous studies have independently evaluated the TC model[48,51], rainfall model[56,76], and storm tide model[70] by comparing against historical observations. Here, we additionally evaluate the ability of our models to reproduce observed dependence between TC rainfall and storm tides. We compare the Kendall rank correlation[79] computed from modeled rainfall and storm tides (derived from reanalysis data) against the Kendall correlation computed from observed storm tides and observed daily rainfall at 31 gauge locations across the coastline (Figure S10). The Kendall correlation coefficient can capture non-linear dependence between two variables by utilizing the relative ranks of each observation rather than the magnitude, and Kendall correlation has been used extensively as a metric to assess dependence between rainfall and storm tides[80-82]. If the modeled rainfall and storm tides from the NCEP synthetic TCs produce a similar correlation coefficient as the observations, this suggests that the models produce joint high (and joint low) events with similar likelihood as the real observed TCs, and thus increase our confidence in the use of our models to project current and future joint hazard.

Based on Figure S10, the model-based correlations match well with the observed correlations, with an overall root mean square error (RMSE) of 0.09 and bias of 0.02 (indicating slight overestimation of rainfall-surge dependence). For the majority of locations the difference between modeled and observed correlations is within +/- 0.1. The model overestimates the correlation for the region between Mississippi and the Florida panhandle. The discrepancy between modeled and observed correlation in this region is likely due to the occurrence of other observed rainfall mechanisms, such as extra-tropical transition or interaction with fronts, that are not simulated by the TC model and cause lower correlation between observed rainfall and storm tides.

Sea Level Rise Projections

We incorporate probabilistic, localized sea level rise projections from ref. [83] for 2100 considering the RCP 8.5 emission scenario. In ref. [83] sea level rise probability distributions are developed for tide gauge locations across the globe by taking into account ice sheet components (Greenland, West Antarctic, and East Antarctic), glacier and ice cap surface mass balance, thermal expansion and oceanographic processes, land water storage, and other non-climatic factors. Sea level changes due to thermal expansion and oceanographic processes are based on ensemble mean projections from a suite of CMIP5 GCMs. For each point along the coastline, we select the nearest tide gauge and adopt the probability distribution specified by ref. [83].

We calculate total sea level for each TC by randomly drawing from the SLR distributions and superimposing on the modeled storm tides for computational efficiency. The assumption of linearity between SLR and storm tides is a reasonable approximation of extreme sea levels, but nonlinear interactions between SLR and storm tides can be significant in complex local areas, particularly small bays and estuaries[84,85]. We also treat TC climatology change and SLR as independent, although they may be significantly correlated. Ref [86] found a significant correlation between SLR and changes in power dissipation index (an integrated measure of TC intensity, frequency, and duration) for the North Atlantic, suggesting that large increases in mean sea level are more likely to co-occur with larger increases in TC hazard. By neglecting correlation between SLR and climatology changes our results may underestimate the composite (weighted-average) change in climatology and SLR, and consequently represent a conservative estimate of joint hazard change.

Statistical Analysis of Joint Hazard

We conduct statistical analysis on the pairs of maximum modeled storm tides (or storm tides plus SLR) and maximum 24-hr rainfall accumulation at each location along the coastline to quantify their marginal and joint hazard.

The marginal distributions of both rainfall and storm tides are often characterized by a long tail representing the rare but extreme events[52,53]. The heavy tail can be modeled with a Peaks-Over-Threshold approach, where the probability above a high threshold is estimated by a Generalized Pareto (GP) distribution[87]. We fit marginal GP distributions using the maximum likelihood method[87] for the rainfall and storm tides at each location, and the threshold is set by numerically minimizing the root mean square error between the empirical quantiles and the theoretical quantiles. According to bivariate extreme value theory, a logistic model can be used to estimate the joint distribution of two GP variables such that their bivariate CDF takes the form[87,88]:

$$G(x,y)=\exp\{-(\tilde{x}^{-1/\alpha}+\tilde{y}^{-1/\alpha})^{\alpha}\} \quad (1)$$

Where $\tilde{x}$ and $\tilde{y}$ are the Fréchet-transformed versions of the variables x and y, and α is a parameter that quantifies the strength of the dependence between the variables ($\alpha \rightarrow 0$ signifies complete dependence and α=1 complete independence). At each location we transform the rainfall and storm tide pairs based on their respective marginal distributions and GP thresholds to obtain Fréchet versions of the variables. Then we fit the bivariate distribution using a censored maximum likelihood approach[88] that considers pairs that jointly exceed their GP thresholds (within the "evd" R-package[89]). We additionally ensure that there are at least 20 pairs of joint exceedances to fit the bivariate model. The bivariate logistic model employed here has previously been utilized to model dependence between rainfall and storm surges[88,90-92].

After characterizing the marginal and joint distributions of rainfall and storm tides at each coastline location, we quantify the return period (inverse of the annual exceedance probability) of jointly extreme events. For each location, we model TC occurrence as a Poisson Process with arrival rate λ per year. The basin arrival rate is a parameter of the TC model[20] and is calibrated to match the observed occurrence rate in the North Atlantic basin for the historical period. The location-specific arrival rate (λ) is an adjustment of the basin arrival rate according to the proportion of storms passing within 200 km of each location. We define x_T, y_T as the marginal 100-year storm tide and 100-year rainfall, defined in the historical period. Then the return period of an event that jointly exceeds x_T and y_T (henceforth labeled JRP) is calculated as follows:

$$JRP=\frac{1}{1-e^{-\lambda P}} \quad (2)$$

Where P is the joint exceedance probability:

$$P=1-\Pr(X\le x_T)-\Pr(Y\le y_T)+G(x_T,y_T) \quad (3)$$

Where G is defined in equation 1.

We quantify JRP under the current and future storm climates, by fitting marginal and joint distributions to storm tide and rainfall pairs from NCEP or each GCM-derived storm dataset. We estimate the sampling uncertainty bounds of the JRP estimates by implementing a bootstrapping approach with 500 iterations for each location and each GCM. For each iteration, we re-sample (with replacement) pairs of modeled storm tides and rainfall, fit the univariate and joint distributions and re-calculate JRP.

Attribution of Changes in Joint Hazard

To quantify the isolated impact of various climate factors on changes in joint rainfall-surge hazard, we adjust a single factor at a time and then re-calculate JRP. To quantify the isolated impact of SLR on changes in JRP, we randomly draw SLR values from location-specific probability distributions[18] and add them to the historical rainfall-storm tide pairs. The impact of changes in future storm frequency is quantified by simply changing the value of λ in Equation 2 to reflect the future period frequency. Because storm tide and rainfall are dependent, we quantify the impact of changes in (1) marginal rainfall distribution, (2) marginal storm tide distribution, and (3) dependence between hazards, through quantile-matching. Specifically, we calculate $F_{r,h}$ and $F_{s,h}$, which are the historical rainfall (r_h) and storm tide (s_h) cumulative distribution functions (CDFs), and $F_{r,f}$ and $F_{s,f}$, which are the future CDFs. Given historical pairs of rainfall and storm tide (r_h, s_h) we can evaluate the impact of changes in rainfall hazard by changing r_h values to $r_h^* = F_{r,f}^{-1}(F_{r,h}(r_h))$ so that the magnitude of rainfall is increased according to the future period rainfall distribution but the storm tide (s_h) values and dependence between hazards are unchanged. We similarly calculate the storm tide values (s_h^*) while keeping the rainfall values (r_h) constant to evaluate the impact of increases in storm tide on the JRP change. The methodology above guarantees the rank correlation between TC rainfall and surge is unchanged. To measure the impact of changes in hazard dependence (α in Equation 1), we adjust the future rainfall and storm tide pairs (r_f, s_f) as follows: $r_f^* = F_{r,h}^{-1}(F_{r,f}(r_f))$, $s_f^* = F_{s,h}^{-1}(F_{s,f}(s_f))$. The adjusted values of rainfall and storm tide are reduced according to their historical distributions, but the dependence between hazards is based on the future period climatology.

Data availability statement:

The hazard data generated from this study are deposited to the NSF DesignSafe-CI and can be accessed online (https://doi.org/10.17603/ds2-gv07-kf03)[93]. Downscaled TC track information can be obtained by contacting K.E.

Code availability statement:

The codes for marginal and bivariate extreme value analysis, and for visualization are deposited to the NSF DesignSafe-CI and can be accessed online (https://doi.org/10.17603/ds2-gv07-kf03)[93].

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