Probabilistic Tropical Cyclone Surge Hazard Under Future Sea-Level Rise Scenarios: A Case Study in The Chesapeake Bay Region, USA.

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Abstract

Storm surge flooding caused by tropical cyclones is a devastating threat to coastal regions, and this threat is growing due to sea-level rise (SLR). Therefore, accurate and rapid projection of the storm surge hazard is critical for coastal communities. This study focuses on developing a new framework that can rapidly predict storm surges under SLR scenarios for any random synthetic storm of interest and assign a probability to its likelihood. The framework leverages the Joint Probability Method with Response Surfaces (JPM-RS) for probabilistic hazard characterization, a storm surge machine learning model, and a SLR model. The JPM probabilities are based on historical tropical cyclone track observations. The storm surge machine learning model was trained based on high-fidelity storm surge simulations provided by the U.S. Army Corps of Engineers (USACE). The SLR was considered by adding the product of the normalized nonlinearity, arising from surge-SLR interaction, and the sea-level change from 1992 to the target year, where nonlinearities are based on high-fidelity storm surge simulations and subsequent analysis by USACE. In this study, this framework was applied to the Chesapeake Bay region of the U.S. and used to estimate the SLR-adjusted probabilistic tropical cyclone flood hazard in two areas: One is an urban Virginia site, and the other is a rural Maryland site. This new framework has the potential to aid in reducing future coastal storm risks in coastal communities by providing robust and rapid hazard assessment that accounts for future sea-level rise.

Keywords Probabilistic hazard assessment · Joint probability method · Machine learning · Sea level rise · Storm Surge

Abbreviations

ADCIRC	ADvanced CIRCulation model
AEP	Annual Exceedance Probability
CNN	Convolutional Neural Network
HURDAT2	HURricane DATa 2nd generation
JPM	Joint Probability Method
JPM-OS	Joint Probability Method with Optimal Sampling
JPM-RS	Joint Probability Method with Response Surfaces
MBE	Mean Bias Error
ML	Machine Learning
MSL	Mean Sea Level
NACCS	North Atlantic Comprehensive Coastal Study

NOAA	National Oceanographic and Atmospheric Administration
PBL	Planetary Boundary Layer numerical model
PCA	Principal Component Analysis
RMSE	Root Mean Square Error
SLR	Sea Level Rise
SRR	Storm Recurrence Rate
SWAN	Simulating Waves Nearshore model
TC	Tropical Cyclone
USACE	U.S. Army Corps of Engineers

1. Introduction

Storm surges due to tropical cyclones (TCs) are a major threat to coastal communities, and more frequent intense storms (Emanuel 2013; Knutson et al. 2019) are projected to occur due to global warming impacts (Sweet et al. 2017). In the United States, around 2,500 people lost their lives from Atlantic tropical cyclones from 1963 to 2012, and storm surges were responsible for about 50% of these deaths (Rappaport 2014). Nonetheless, millions of people still live in coastal regions, and more people are moving to the coasts every year.

To reduce storm surge damage, a robust probabilistic storm surge hazard assessment is important. There are several statistical approaches to assessing storm surges (Resio et al. 2017). The joint probability method considers all plausible combinations of TC parameters and has been widely adopted in the United States for probabilistic tropical cyclone surge characterization. However, one of the key challenges of the JPM is the computational burden of the physics-based numerical simulations to estimate storm surges. Thus, many studies used the Joint Probability Method with Optimal Sampling (JPM-OS) to reduce the number of TCs required for populating the parameter space by optimizing the sampling of the storm parameters (Resio et al. 2007; Toro et al. 2008; Vickery and Blanton 2008).

In recent years, machine learning models have been developed in order to predict storm surges rapidly with relatively high accuracy, compared to the physics-based numerical models (e.g., Al Kajbaf and Bensi 2020; Kyprioti et al. 2021; Lee et al. 2021). Although these machine learning models have paved the way for the direct application of JPM in storm surge hazard assessment, there are only few related studies.

Using the advantage of the ML model , we adopt the Joint Probability Method (Myers, 1975) with Response Surface (JPM-RS) for its simultaneous ability to capture the natural structure present in storm surge response (Resio et al. 2017) and to provide a statistically stable hazard estimate (Irish et al. 2009, Irish et al. 2011).

This study proposes a framework that provides a robust and rapid SLR-adjusted probabilistic tropical cyclone flood hazard assessment. The basic function of the framework consists of several processes, such as generating many possible combinations of TC parameters, determining each combination's probability, and estimating each combination's flood elevation for the SLR scenarios of interest. From this information, the probabilistic flood hazard is estimated over a range of annual exceedance probabilities. The following sections first present the datasets and analysis of each component of the framework, then present the case study results of the framework.

2. Study Area and Data

The Chesapeake Bay is the largest estuary on the East Coast, US, and is in the Mid-Atlantic coastal region. The Chesapeake Bay is adjacent to several high-density metropolitan areas, industrial areas, and residential areas with complex transportation networks (Sanchez 2012). Over the past 20 years, the Chesapeake Bay has been impacted several times by tropical cyclones (Garzon et al. 2018), and more than 20 hurricanes and tropical cyclones have passed the Chesapeake Bay (Li et al. 2020). Significant hurricanes impacting the region in recent decades include: (1) Hurricanes Isabel (2003), (2) Irene (2011), and (3) Sandy (2012) (Callahan et al. 2021). For example, the estimated total economic loss from Hurricane Isabel (2003) was approximately $3.37 billion, and Isabel was directly responsible for 17 deaths (NOAA 2004). In addition, the Chesapeake Bay is vulnerable since the sea level rise leads to more extreme coastal hazards in this region (Hallegatte et al. 2013; 2014). The sea level of the Chesapeake Bay increased by 3-4 mm per year over the twentieth century; This is about two times larger than the global SLR average (Zervas 2001; 2009). Herein, we used two NOAA tide gauge stations to show the future SLR impacts. The Sewells Point (Station ID: 8638610) in Virginia is used to represent the urban Virginia site, and it sits in the city of Norfolk in Virginia (Loftis 2018). The Cambridge (Station ID: 8571892) is used to represent the rural Maryland site since Cambridge is located relatively rural area in Maryland compared to Sewells Point.

To develop the JPM, we used historical TC datasets and the historical TC datasets collected from the National Oceanographic and Atmospheric Administration (NOAA) National Hurricane Center HURDAT2 (HURricane DATa 2nd generation) for the 1938 – 2013 period (Landsea et al. 2015). We also used the marginal distributions of TC parameters which are analyzed by the USACE based on the historical TC datasets from NOAA (Nadal-Caraballo et al. 2015). The ML model (Lee et al. 2021) was trained based on the U.S. Army Corps of Engineers' North Atlantic Comprehensive Coastal Study (NACCS) synthetic tropical cyclone surge database (Figure 1, Cialone et al. 2015). The NACCS database contains high-fidelity storm surge simulations for 1,031 synthetic tropical cyclones, simulated using ADCIRC coupled with SWAN (Luettich et al. 1992; Dietrich et al. 2011) with a PBL model for wind/pressure forcing (Thompson and Cardone 1996); where we made use of 3,111 model save points within the Chesapeake Bay study region. To demonstrate the application of sea level rise in the framework, we used the 2017 NOAA intermediate sea-level rise projections. The global mean sea level rise range for 2100 is discretized by 0.5m increments and aligned with emissions-based, conditional probabilistic storylines and global model projects. The intermediate scenario corresponds to global mean sea level rise of 1.0m (Sweet et al. 2017). In this study, the intermediate sea level rise scenarios are applied as sea level change values from the base year to the year of interest.

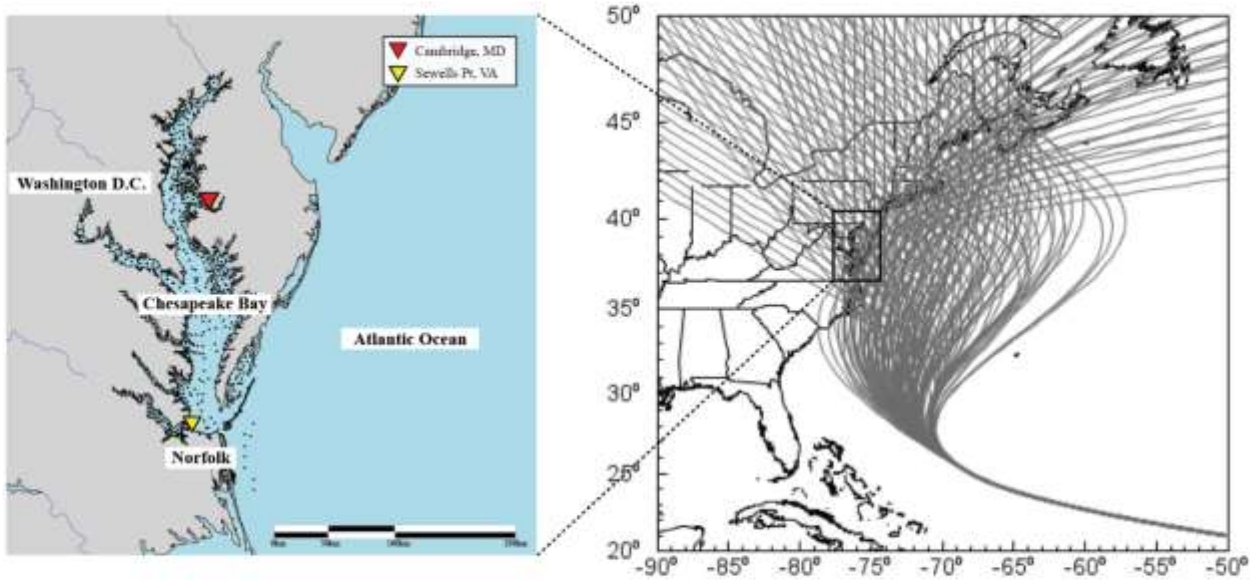

Figure 1 Study area: The left map represents the Chesapeake Bay, Maryland and Virginia, USA and the two study stations. In the left map, the black dots represent the NACCS save point. The red triangle represents Cambridge, Maryland and the yellow triangle represents Sewells Pt, Virginia. In the right map, the grey lines are the storm tracks used in the U.S. Army Corps NACCS study (Source: Nadal-Caraballo et al., 2015).

3. Methodology

The framework consists of three components: (1) JPM, (2) ML model, and (3) SLR model (Figure 2). First, the JPM creates the six TC parameter time series and probabilities of each TC. Secondly, the ML model predicts the peak storm surges in the study areas. And lastly, the SLR model applies the impacts of the sea-level change under different future SLR scenarios.

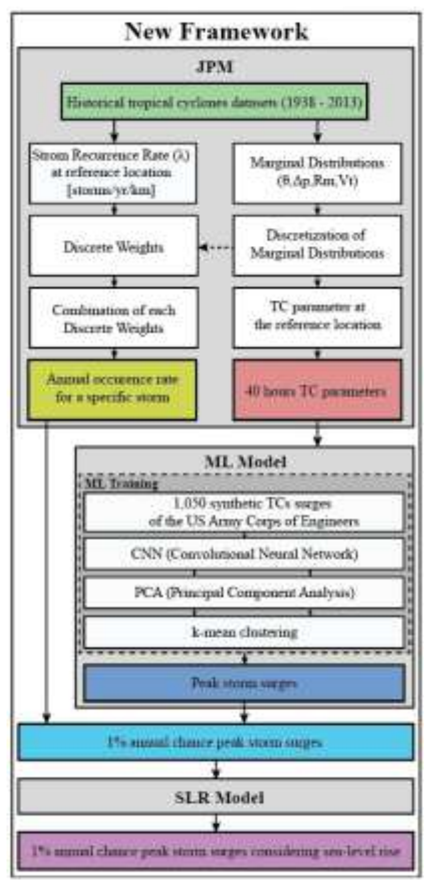

Figure 2 Computational flow of the framework

3.1 Joint Probability Method with Response Surfaces (JPM-RS)

The JPM is a method to estimate flood elevation due to storm surges (Divoky et al. 2007). The JPM attempts to consider the range of possible combinations of TC parameters at the coastal reference line and it is widely used in the United States to estimate the annual exceedance probabilities of storm surges (Eq. 3). However, computational time using high-fidelity surge model precludes simulation of all storm possibilities represented within the JPM parameter space (Toro et al. 2010). For this reason, the joint probability method with optimal sampling (JPM-OS) has been widely applied to represent storm surges within the parameter space based on a small number of simulated storms (Resio et al. 2007; Toro et al. 2008; Vickery and Blanton 2008). A ML model was developed in 2021 (Lee et al. 2021), and the ML model can rapidly predict the pick storm surges. By taking advantage of the ML model, we applied the JPM to create the TC parameter in time-series and probabilities of synthetic TCs. In practice, two approaches have been commonly used to minimize the computational burden when the JPM for tropical cyclone hazard assessment: (1) surface response function, and (2) Bayesian quadrature. The major difference between those two approaches is that the surface response function approach creates continuous surfaces, and the Bayesian quadrature approach optimizes a set of probability masses. Another difference between those two approaches is that the surface response function can be interpolated or extrapolated on a fine scale, but the Bayesian quadrature approach cannot (Resio et al. 2017). Herein, we used a response surface approach (JPM-RS) to specify surge within the parameters space. In JPM-RS, six parameters are considered (latitude and longitude at the landfall reference location, heading direction, central pressure, radius of maximum winds, and translational speed). The response surface is derived using a machine-learning model developed in 2021 (Lee et al. 2021). Using the ML model, we discretized the JPM TC parameter space into 10,000 unique synthetic storm track combinations, then estimated storm surge for each of these 10,000 unique storms using the ML model.

To calculate the probability of synthetic tropical cyclones, we used the SRR and discrete weights of four TC marginal distributions (Eq. 1).

$$p_n = \lambda_n \int_{dL(\theta)}^{dU(\theta)} f(\theta)\, d\theta \times \int_{dL(p)}^{dU(p)} f(p)\, dp \times \int_{dL(R)}^{dU(R)} f(R)\, dR \times \int_{dL(V)}^{dU(V)} f(V)\, dV \tag{1}$$

Where: p_n=probability of synthetic tropical cyclones, λ_n=storm recurrence rate at the best reference location, dL=lower value of discretization of TC marginal distribution, dU=upper value of discretization of TC marginal distribution.

3.1.1 Storm Recurrence Rate (SRR)

Statistical computation of storm recurrence rate can be estimated using several different approaches. In this study, we applied a circular window capture zone with a Gaussian kernel function (Chouinard and Liu 1997) based on the historical TCs in the HURDAT2 database with $\Delta p \geq 28$ hPa within the 1938–2013 period (Eqs. 2 & 3).

$$\lambda = \frac{1}{T}\sum_{i}^{n} w(d_i) \tag{2}$$

$$w(d_i) = \frac{1}{\sqrt{2\pi}h_d} \exp\left[-\frac{1}{2}\left(\frac{d_i}{h_d}\right)^2\right] \tag{3}$$

Where λ = SRR in storms/yr/km, T: record length in year (1938-2013), $w(d_i)$=distance-adjusted weights from the Gaussian probability density function (km^{-1}), d_i=distance from location of interest to a storm track point (km), h_d=optimal kernel size (km). In applying Eqs. 2 and 3 the HURDAT database, the storm recurrence rate (SRR) at the reference location is determined to be 0.000279 storms/yr/km (0.1116 storms/yr).

We chose the circular window capture zone as follows. The coastal reference line represents the coastline where the TCs make landfall. The NACCS-defined coastal reference line is located 250 km from the coastal reference line. (Nadal-Caraballo et al. 2015). The coastal reference line consists of with coastal reference points (Figure 3). In this study, we chose one point of the coastal reference point as the best reference point (Latitude: 37.9208˚N and Longitude: 75.3853˚W) that has the minimum distance from the points of the coastal reference point to any save points in the study area. Using Eqs. 2 and 3, the storm recurrence rate (SRR) at the reference location was 0.000279 storms/yr/km (0.1116 storms/yr). We used a 200 km capture zone size, which covers the Chesapeake Bay region, and the maximum distance from the reference point to the furthest save point in the Chesapeake Bay region was 198 km (Figure 3). Then we generated the synthetic TCs passing through the capture zone centered at the best reference point.

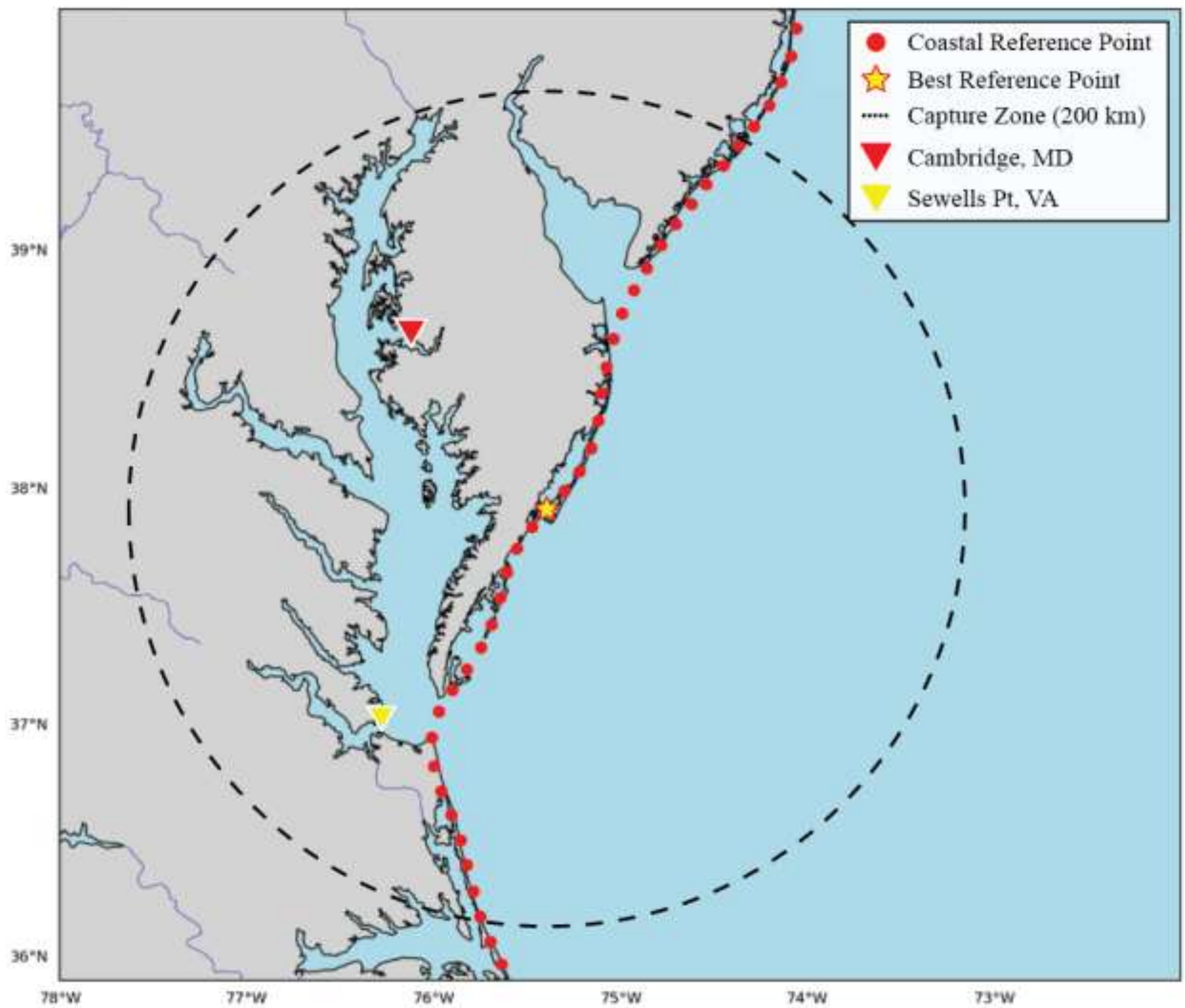

Figure 3 Coastal reference points with 200 km capture zone centered at the best reference point. The red circles represent the coastal reference points. The yellow star represents the best reference point. The dashed black line represents the 200 km capture zone. The red triangle represents the Cambridge NOAA station in Maryland and the yellow triangle represents the Sewell Pt NOAA station in Virginia.

3.1.2 Marginal TC parameter probability distributions

To develop synthetic tropical storms including landfalling and bypassing storms covering the entire Virginia-to-Maine coastal region, four TC parameter s(heading direction, central pressure, radius of maximum winds, and translational speed) are used, and the tracks of the synthetic TCs were decided based on the SRR of the coastal reference points and natural spline curve. The NACCS divided the northeast Atlantic coastal region into three subregions for the computation of TC statistics (Nadal-Caraballo et al. 2015) and the capture zone centered at the best reference point (Figure 3) located within the NACCS Subregions 2 (Cialone et al. 2015). Therefore, herein we applied the marginal distribution parameters of four TC parameters of the NACCS Subregion 2 (Table 1; Nadal-Caraballo et al. 2015). The storm recurrence rates of TCs passing the capture zone are calculated based on the HURDAT2 database for the 1938-2013 period (Landsea et al. 2015), except for weak storms (Δp < 28 hPa). In this study, we created 10,000 synthetic storms passing the capture zone, and we discretized four TC marginal distributions into ten.

Table 1 TC marginal distribution type and parameters (Source: Nadal-Caraballo et al. 2015)

	Probability Distribution Type	Marginal distribution parameters
Heading direction (θ)	Normal distribution	μ (deg): 16.48 σ (deg): 36.17
Central pressure deficit (Δp)	Doubly truncated Weibull distribution	U (hPa): 35.77 k: 1.00 Δp_1(hPa): 25 Δp_2(hPa): 93
Radius of maximum winds (R_m)	Lognormal distribution	μ (km): 4.22 σ (km): 0.45
Translational speed (V_t)	Normal distribution	μ (km/h): 44.05 σ (km/h): 16.06

Where: μ=mean value of marginal distribution, σ=standard deviation of marginal distribution, U=scale parameter, k=shape parameter, Δp_1=lower limit of Δp, and Δp_2=upper limit of Δp

3.2 ML model

The ML model called C1PKNet was applied to the framework (Lee et al. 2021). This ML model consists of three components: (1) k-means clustering, (2) principal component analysis (PCA), and (3) one-dimensional convolutional neural network (CNN). Firstly, the k-means clustering groups the storm surge data among geospatial points with similar storm surges responses to increase the accuracy of the ML model. Secondly, the PCA reduces the dimensionality of the clustered storm surge data. Thirdly, the CNN captures the features of TC conditions over time. By taking advantage of CNN, this ML model allows the model considers the time-series of TC parameters rather than consider one representative time-step. This ML model was trained using 1,031 synthetic TCs (Figure 1) and it can rapidly predict the peak storm surges in the Chesapeake Bay region (3,111 save points) from the 40-hr TC parameter time series. This ML model was evaluated by not only the synthetic TCs of the NACCS database but also three observed historical hurricanes: 1. Isabel (2003), (2) Irene (2011), and (3) Sandy (2012).

To validate the ML model for this study, we compared between peak storm surge of 1,031 synthetic TCs from the ML model and peak storm surges of 1,031 synthetic TCs from the physics-based numerical model (ADCIRC) at two NOAA stations (Sewells Pt, VA and Cambridge, MD). Figure 4 shows the comparison plots of two areas. The root mean square errors (RMSE) at Sewells Pt and Cambridge are 0.11m and 0.07m. The mean bias errors (MBE) at Sewells Pt and Cambridge are 0.03m and 0.02m. Furthermore, the R^2 values at Sewells Pt and Cambridge are about 0.96 and 0.94, respectively.

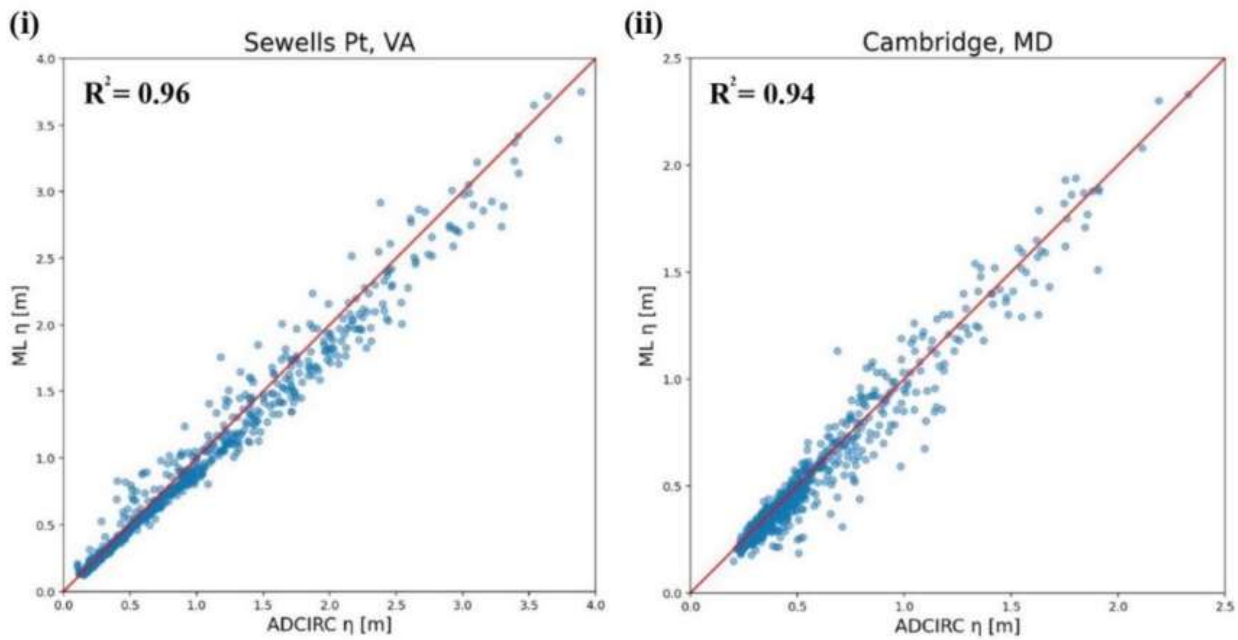

Figure 4 Comparison between peak storm surges of 1,031 synthetic TCs from physics-based numerical model and peak storm surges of 1,031 synthetic TCs from ML at two NOAA stations (1) comparison between numerical model and ML model at Sewells Pt, Virginia (2) comparison between numerical model and ML model at Cambridge, Maryland

3.2.1 Prelandfall and Postlandfall of TCs

As an input of the ML model of framework, we generated 40-hour TC parameters of 10,000 synthetic TCs passing the capture zone (Figure 3). In this section, we use the term "coastal reference point" because the TCs combinations apply to this point . The difference between coastal reference line and coastal reference point is already explained in section 3.1.1. All tracks of 10,000 synthetic TCs are divided into the 30 hours before passing the coastal reference point and 10 hours after passing the coastal reference point. The central pressure, transitional speed, and radius of maximum winds are constant until the coastal reference point (Vickery and Wadhera 2008). For the heading direction and TC tracks, all landfall tracks apply a constant heading direction after passing the coastal reference point. A natural spline curve is applied to generate the tracks from the beginning location of synthetic tropical cyclones to the coastal reference point. Since no statistically significant trend was found from the historical records of central pressure data, a 5% decay rate of central pressure deficit (Δp) was applied from the coastal reference points of the synthetic TCs passing the capture zone to the landfall location following NACCS study (Nadal-Caraballo et al. 2015). Again, following the NACCS study (Nadal-Caraballo et al. 2015), the radius of the maximum winds depends on the central pressure deficit from the coastal reference point to landfall. The transitional speed is constant after passing the coastal reference point.

3.3 Annual Exceedance Probability of Flooding

Once we predicted the peak storm surges for all 10,000 synthetic storms using the ML model, the annual exceedance probability (AEP) for storm surge was estimated using Eq. 4. We calculated the AEP of each save point using the Heaviside function (Resio et al. 2017). In Eq. 4, the uncertainty of output of the JPM, ML model, and the high-fidelity surge simulations were not considered.

$$\mathrm{AEP}(\eta) \approx \sum_{\mathrm{i}=1}^{k} p_i \mathrm{H}[\hat{\eta}_i - \eta] \tag{4}$$

Where: p_i=probability of i[th] synthetic tropical cyclone (Eq. 1), $\hat{\eta}_i$=modeled surge value by the i[th] storm, H[$\hat{\eta}_i$-η], η=target peak storm surge, k=total number of synthetic TCs

3.4 SLR model

To project the impact of SLR on tropical cyclone flooding in the study area, we used Eq. 5 (Bilskie et al., 2014; Smith et al., 2010).

$$\eta = \eta_o + SLR(1 + NNL) \tag{5}$$

Where: η=storm surge, relative to mean sea level (MSL) in the base year (1992 for NACCS), η_o=storm surge in the base year, SLR: sea level rise from the base year to the year of interest, and NNL: normalized nonlinearity index (Bilskie et al. 2014).

The impact of SLR on peak storm surge is not linear and will likely be substantially biased high or low (Bilskie et al. 2014; Liu et al. 2019, Smith et al. 2010; Mousavi et al. 2011; Nadal-Caraballo et al. 2015). Therefore, we applied the normalized nonlinearity index (Bilskie et al., 2014) of each save point in the Chesapeake Bay, as reported in the NACCS database (Cialone et al. 2015; Nadal-Caraballo et al. 2015). The annual exceedance tropical cyclone surges at the locations of interest were adjusted in reference to the 1983-2001 tidal epoch MSL datum (Cialone et al. 2015).

4. Framework Application

Using the framework, we created peak storm surge probabilistic hazard curves under different SLR scenarios in two NOAA stations. Furthermore, we applied linear interpolation to extract several peak storm surge annual exceedance probabilities (AEP) from the hazard curves. In this study, we used the SLR values for two NOAA stations based on NOAA Intermediate sea-level change projections (Table 2; Sweet et al., 2017). Figure 5 presents the map of the 1% AEP peak storm surges in the Chesapeake Bay and the histogram of the number of geographic stations of the 1% AEP peak storm surges. As shown in Figure 5, the area near the urban Virginia station has the greater 1% AEP peak storm surges compared to the area near the rural Maryland station.

In addition, the urban Virginia area has greater SLR values than the rural Maryland area in the future (Table 2).

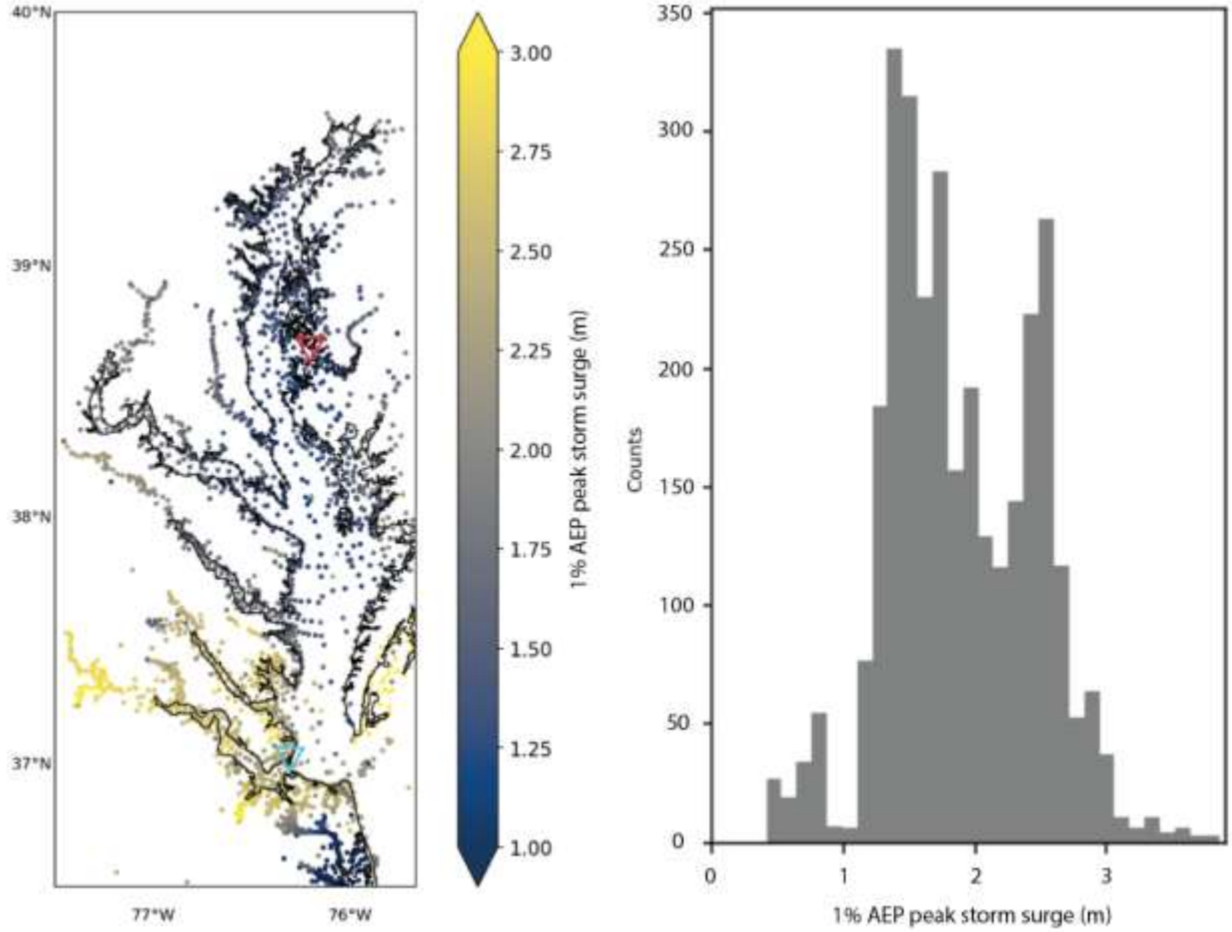

Figure 5 1% AEP peak storm surge map and histogram from the framework under current-day sea level condition. The left figure shows a map of 1% AEP peak storm surge in Chesapeake Bay. The right figure shows histogram of counts of 1% AEP peak storm surge in Chesapeake Bay. The bluish triangle symbol represents Sewell Pt station in Virginia and the red triangle symbol represents Cambridge station in Maryland. Astronomical tides, precipitation and uncertainty are not considered.

Table 2 Table of SLR (cm) from the base year (1992) to the year of interest in two NOAA stations.

Year of interest	Sewells Point (ID:8638610)	Cambridge (ID:8571892)
2000	3	3
2030	33	31
2060	73	68
2090	123	117

Figure 6 shows the hazard curves, namely annual exceedance probability (x-axis) versus peak storm surges at the two NOAA stations (y-axis). This case study indicates that the SLR-adjusted 1% AEP peak storm surge will be 3.11 m in 2060 in Urban Virginia, which is about 26% greater than the 1% AEP peak storm surge based on current-day mean sea level (MSL). The SLR-adjusted

1% AEP peak storm surge will be 2.30 m in 2060 in Rural Maryland, which is about 41% greater than the 1% AEP peak storm surge based on the current-day mean sea level (MSL).

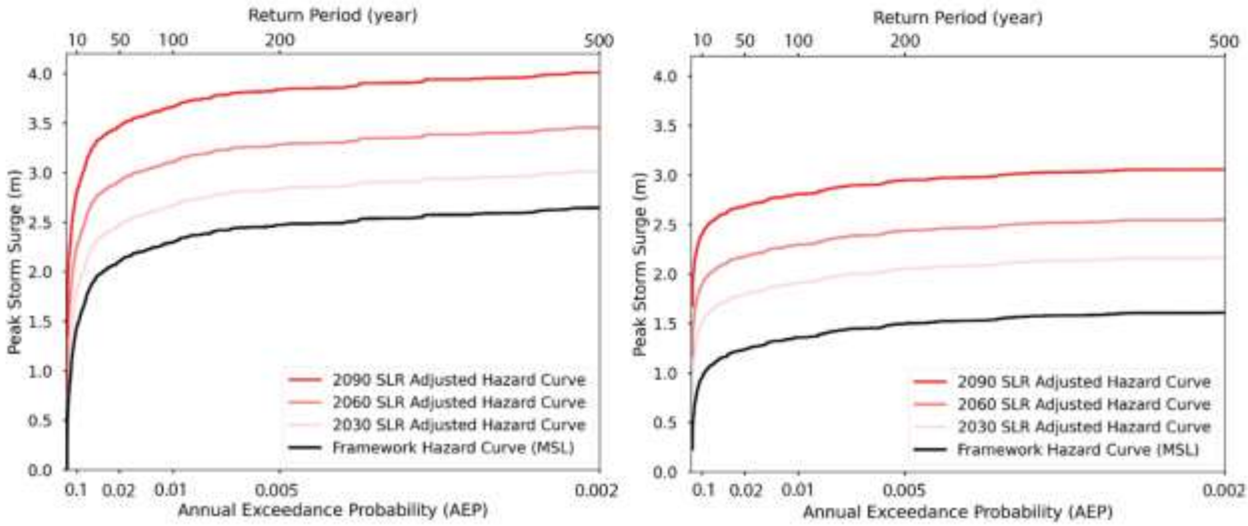

Figure 6 Hazard Curves without uncertainty analysis under future SLR scenarios. (i) Hazard Curves at Sewells Pt, VA. (ii) Hazard Curves at Cambridge, MD. Astronomical tides, precipitation and uncertainty are not considered.

5. Discussion and Conclusions

This paper presents a robust and rapid framework that consists of three models: (1) joint probability method, (2) machine learning model, and (3) sea-level rise model. The framework provides robust and rapid hazard assessment, and has been demonstrated in the Chesapeake Bay, USA region. The framework generates many possible combinations of synthetic TCs inside the capture zone, determining each combination's storm surges using the ML model and estimating the AEP for storm surges under SLR scenarios of interest. For this study, 10,000 combinations of synthetic TCs were generated. The framework applied the sea level change on the 1% AEP peak storm surges in two areas using the SLR model. This case study indicates that the 1% AEP peak storm surge (MSL) in Urban Virginia is greater than in Rural Maryland and the SLR values from the base year to the year of interest (2030, 2060, and 2090) in Urban Virginia is greater than Rural Maryland. Nonetheless, the percent change in 1% AEP peak storm surge in response to SLR in Urban Virginia (26% by 2060) is smaller than in Rural Maryland (41% by 2060).

Although the framework can provide rapid storm surge hazard assessment in the Chesapeake Bay region, there are still several factors that need to be tested. First, a limitation of this study is the neglect of uncertainty in tropical cyclone hazard assessment. Therefore, for a more reliable tropical cyclone hazard assessment, an uncertainty analysis related to the framework has to be conducted in future work. Secondly, in this study, we used only a 200 km capture zone size centered at the best reference point. This capture zone included the entire Chesapeake Bay region, but this means we only generated the combinations of synthetic TCs passing this capture zone. Therefore, the influence of storms outside the capture zone is not captured in the hazard curves; there is a need to investigate the impact of capture zone size on the flood hazard estimate. Thirdly, the framework provides a tropical cyclone flood hazard assessment using 10,000 synthetic TCs. Taking advantage of the framework, we can increase the total synthetic TCs (e.g., from 10^4 to 10^5 or 10^6 synthetic TCs) and determine how the total number of synthetic TCs, namely the degree to which the JPM probability space is resolved, affects the results. Lastly, astronomical tides influence coastal flooding, but this factor was not considered in this study. Likewise, compound storm surge and precipitation flooding are known to be significant in some regions of the Chesapeake study area. Therefore, future study is needed to evaluate the interaction between TCs peak storm surges, astronomical tide, and precipitation in the Chesapeake Bay and to integrate precipitation and tides in the hazard assessment.

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References

Al Kajbaf, A., & Bensi, M. (2020). Application of surrogate models in estimation of storm surge: A comparative assessment. Applied Soft Computing, 91, 106184.

Bilskie, M. V., Hagen, S. C., Medeiros, S. C., & Passeri, D. L. (2014). Dynamics of sea level rise and coastal flooding on a changing landscape. Geophysical Research Letters, 41(3), 927-934.

Blanton, B. O., & Vickery, P. J. (2008). North Carolina Coastal Flood Analysis System Hurricane Parameter Development. Technical Report. TR-08-06. Renaissance Computing Institute.

Callahan, J. A., Leathers, D. J., & Callahan, C. L. (2021). Skew Surge and Storm Tides of Tropical Cyclones in the Delaware and Chesapeake Bays for 1980–2019. Frontiers in Climate, 3, 610062.

Chouinard, L. E., & Liu, C. (1997). Model for recurrence rate of hurricanes in Gulf of Mexico. Journal of Waterway, Port, Coastal, and Ocean Engineering, 123(3), 113-119

Cialone, M. A., Massey, T. C., Anderson, M. E., Grzegorzewski, A. S., Jensen, R. E., Cialone, A., ... & McAlpin, T. O. (2015). North Atlantic Coast Comprehensive Study (NACCS) coastal storm model simulations: Waves and water levels. Engineer Research and Development Center Vicksburg MS Coastal and Hydraulic Lab.

Dietrich, J. C., Zijlema, M., Westerink, J. J., Holthuijsen, L. H., Dawson, C., Luettich Jr, R. A., ... & Stone, G. W. (2011). Modeling hurricane waves and storm surge using integrally coupled, scalable computations. Coastal Engineering, 58(1), 45-65.

Divoky, D., & Resio, D. T. (2007, November). Performance of the JPM and EST methods in storm surge studies. In 10th International Workshop on Wave Hindcasting and Forecasting, and Coastal Hazard Symposium, North Shore, Oahu, Hawaii.

Emanuel, K. A. (2013). Downscaling CMIP5 climate models shows increased tropical cyclone activity over the 21st century. Proceedings of the National Academy of Sciences, 110(30), 12219-12224.

Garzon, J. L., Ferreira, C. M., & Padilla-Hernandez, R. (2018). Evaluation of weather forecast systems for storm surge modeling in Chesapeake Bay. Ocean Dynamics, 68(1), 91-107.

Hallegatte, S., Green, C., Nicholls, R. J., & Corfee-Morlot, J. (2013). Future flood losses in major coastal cities. Nature Climate Change, 3(9), 802-806.

Ho, F. P., & Myers, V. A. (1975). Joint Probability Method of Tide Frequency Analysis Applied to Apalachicola Bay and St. George Sound, Florida. NOAA Technical Report. NEW 18. 43 pp

Irish, J. L., Resio, D. T., & Cialone, M. A. (2009). A surge response function approach to coastal hazard assessment. Part 2: Quantification of spatial attributes of response functions. Natural hazards, 51(1), 183-205.

Irish, J. L., Resio, D. T., & Divoky, D. (2011). Statistical properties of hurricane surge along a coast. Journal of Geophysical Research: Oceans, 116(C10).

Knutson, T., Camargo, S. J., Chan, J. C., Emanuel, K., Ho, C. H., Kossin, J., ... & Wu, L. (2019). Tropical cyclones and climate change assessment: Part I: Detection and attribution. Bulletin of the American Meteorological Society, 100(10), 1987-2007.

Kyprioti, A. P., Taflanidis, A. A., Nadal-Caraballo, N. C., & Campbell, M. (2021). Storm hazard analysis over extended geospatial grids utilizing surrogate models. Coastal Engineering, 168, 103855.

Landsea, C., Franklin, J., & Beven, J. (2015). The revised Atlantic hurricane database (HURDAT2). NOAA/NHC (nhc.noaa.gov).

Lee, J. W., Irish, J. L., Bensi, M. T., & Marcy, D. C. (2021). Rapid prediction of peak storm surge from tropical cyclone track time series using machine learning. Coastal Engineering, 170, 104024.

Li, M., Zhang, F., Barnes, S., & Wang, X. (2020). Assessing storm surge impacts on coastal inundation due to climate change: case studies of Baltimore and Dorchester County in Maryland. Natural Hazards, 103(2), 2561-2588.

Liu, Y., Asher, T. G., & Irish, J. L. (2019). Physical drivers of changes in probabilistic surge hazard under sea level rise. Earth's Future, 7(7), 819-832.

Loftis, D., Forrest, D., Karaganda, S., Spencer, K., Organski, T., Nguyen, C., & Rhee, S. (2018). StormSense: A new integrated network of IoT water level sensors in the smart cities of Hampton Roads, VA. Marine Technology Society Journal, 52.

Luettich, R.A., Westerink, J.J., Scheffner, N.W., et al., 1992. ADCIRC: An Advanced Three-Dimensional Circulation Model for Shelves, Coasts, and Estuaries. Report 1, Theory and Methodology of ADCIRC-2DD1 and ADCIRC-3DL. Technical Report, Coastal Engineering Research Center (US),

Mousavi, M. E., Irish, J. L., Frey, A. E., Olivera, F., & Edge, B. L. (2011). Global Warming and Hurricanes: the potential impact of hurricane intensification and sea level rise on coastal flooding. Climatic Change, 104(3), 575-597.

Nadal-Caraballo, N. C., Melby, J. A., Gonzalez, V. M., & Cox, A. T. (2015). Coastal storm hazards from Virginia to Maine. Engineer Research and Development Center Vicksburg MS Coastal and Hydraulic Lab.

Nichols, M. M., & Howard-Strobel, M. M. (1991). Evolution of an urban estuarine harbor: Norfolk, Virginia. Journal of Coastal Research, 745-757.

NOAA, 2004. Service Assessment: Hurricane Isabel September 18-19, 2003. Technical Report, National Weather Service, Silver Spring, Maryland

Rappaport, E. N. (2014). Fatalities in the United States from Atlantic tropical cyclones: New data and interpretation. Bulletin of the American Meteorological Society, 95(3), 341-346.

Resio, D. T., Asher, T. G., & Irish, J. L. (2017). The effects of natural structure on estimated tropical cyclone surge extremes. Natural hazards, 88(3), 1609-1637.

Resio, D. T., Boc, S. J., Borgman, L. E., Cardone, V. J., & Dean, R. G. (2007). White paper on estimating hurricane inundation probabilities. Consulting Report prepared by USACE for FEMA. Vicksburg, MS: U.S. Army Engineer Research and Development Center, Coastal and Hydraulics Laboratory.

Sanchez, J. R., G., Kauffman, K., and Reavy, A., Homsey (2012). “Chapter 1.7 - Natural Capital Value” in the Technical Report for the Delaware Estuary and Basin. Partnership for the Delaware Estuary. PDE Report No, (Partnership for the Delaware Estuary). Report No. 17-07, pp 70–75.

Smith, J. M., Cialone, M. A., Wamsley, T. V., & McAlpin, T. O. (2010). Potential impact of sea level rise on coastal surges in southeast Louisiana. Ocean Engineering, 37(1), 37-47.

Sweet, W. V., Kopp, R. E., Weaver, C. P., Obeysekera, J., Horton, R. M., Thieler, E. R., & Zervas, C. (2017). Global and regional sea level rise scenarios for the United States (No. CO-OPS 083).

Thompson, E. F., & Cardone, V. J. (1996). Practical modeling of hurricane surface wind fields. Journal of Waterway, Port, Coastal, and Ocean Engineering, 122(4), 195-205.

Toro, G. R. (2008). Joint probability analysis of hurricane flood hazards for Mississippi. Final report prepared for URS Group Tallahassee, FL in support of the FEMA-HMTAP flood study of the State of Mississippi.

Toro, G. R., Resio, D. T., Divoky, D., Niedoroda, A. W., & Reed, C. (2010). Efficient joint-probability methods for hurricane surge frequency analysis. Ocean Engineering, 37(1), 125-134.

Vickery, P. J., & Wadhera, D. (2008). Statistical models of Holland pressure profile parameter and radius to maximum winds of hurricanes from flight-level pressure and H* Wind data. Journal of Applied Meteorology and climatology, 47(10), 2497-2517.

Zervas, C. (2001). Sea level variations of the United States, 1854-1999 (Vol. 36). US Department of Commerce, National Oceanic and Atmospheric Administration, National Ocean Service.

Zervas, C. (2009). Sea level variations of the United States, 1854-2006. (Vol. 53). US Department of Commerce, National Ocean Service Administration, National Ocean Service.