Method for Estimating Future Hurricane Flood Probabilities and Associated Uncertainty

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Abstract: Reliable hurricane flood probability estimates are essential for effective management and engineering in the coastal environment. However, uncertainty in future climate conditions presents a challenge for assessing future flood probabilities. Studies suggest that in the future, sea-level rise may accelerate, and hurricanes may intensify and occur less or more often. Here, methods are presented for incorporating sea-level rise and future hurricane conditions into extreme-value flood statistics analysis. By considering an idealized coast, surge response functions are used with joint probability statistics to define time-varying continuous probability mass functions for hurricane flood elevation. Uncertainty in the flood estimates introduced by uncertainty in future climate is quantified by considering variance in future climate and sea level projections. It will be shown that future global warming can increase the flood elevation at a given return period by 1–3% per decade, but that climate-related uncertainty only marginally contributes to the overall uncertainty associated with hurricane flood statistics. Finally, it will be demonstrated that adaptive management practices are the most effective means of optimizing future coastal engineering activities in the face of climate change.
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Introduction

The assessment of hurricane flooding risk is an essential component for effective coastal planning and engineering design. Existing methods for evaluating hurricane extreme-value flood probabilities traditionally assume that flood conditions are stationary, such that historical information represents future conditions. However, dynamic changes in the environment, specifically rising sea levels and potential future changes in hurricane intensity and rate of occurrence, mean that future flooding statistics will not be adequately represented by historical conditions alone. In this paper, within a joint probability framework we propose a statistical approach for incorporating future sea level and hurricane climate projections into extreme-value flood projections. By considering an idealized coast, we will show that the added uncertainty in flood statistics due to uncertainty in future conditions is small with respect to other statistical and flood model uncertainty. We will also demonstrate that adaptive approaches, which allow for the reassessment of extreme-value flood probabilities through time, can minimize error in mean flood elevation projections thereby allowing for optimization of coastal planning and design efforts.

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Background

Future Sea-Level Rise and Climate Change

Hurricane flooding statistics depend on climate statistics including hurricane rate of occurrence, landfall location, and intensity as well as mean sea level. Here we consider the influence of long-term climate change on hurricane flooding statistics, and decadal scale climate variation will be neglected. The impact of long-term future climate change is difficult to quantify with a high degree of certainty. However, a growing body of literature supports a future global warming trend, where air and sea surface temperatures are expected to rise over the next century. The Intergovernmental Panel on Climate Change (IPCC 2007) reported sea-surface temperature (SST) rise projections of 1.1–6.4°C over the next century. These warming trends are expected to result in sea-level rise (SLR) and altered hurricane rate of occurrence and intensity.

Mean sea level observations confirm a recent historical global, or eustatic, SLR trend (IPCC 2007; Miller and Douglas 2004; National Oceanic and Atmospheric Administration (NOAA) 2011; White et al. 2005). Eustatic SLR rates are reported to be 0.17–0.18 cm/year over the last century. The vast majority of research on historical SLR trends report an acceleration in SLR, to 0.30 cm/year, in recent years (IPCC 2007). However, tide gauge analysis by Houston and Dean (2011) suggests a slight deceleration in SLR over the last 80 years. With potential global warming, the IPCC (2007) concluded that SLR will most likely accelerate. Since the 2007 IPCC report, recent research points to the possibility of SLR of more than 1 m over the next century when major ice-sheet melting is considered (Overpeck et al. 2006; Pfeffer et al. 2008; Rahmstorf 2007).

The influence of global warming on hurricanes is twofold. First, hurricanes are expected to intensify. Dynamical models and theory both support the hypothesis that tropical cyclones will intensify with global warming (Elsner et al. 2008; Emanuel et al. 2008; Knutson and Tuleya 2008; Vecchi and Soden 2007; Webster et al.

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

2005). Knutson et al. (2010) summarized the results of these studies by concluding that tropical cyclone wind intensity is expected to increase by 2–11% by 2100; the average of all models indicates a mean increase of 6% by 2100. Knutson and Tuleya (2004, 2008) proposed the following simple model for hurricane central pressure intensity, where an average 8% change in central pressure deficit is expected for every 1°C of SST change

$$p_{\Delta SST} = p_o - \left[\left(0.08 + \varepsilon_p\right)\left(\Delta SST + \varepsilon_{\Delta SST}\right)\right]\Delta p \qquad (1)$$

where $p_{\Delta SST}$ = future projected hurricane central pressure; p_o = current-day (2000s) hurricane central pressure; ΔSST = sea-surface temperature change; Δp = far-field barometric pressure less central pressure; ε_p = uncertainty in the fractional change in Δp with ΔSST; and $\varepsilon_{\Delta SST}$ = uncertainty in the ΔSST projection.

In formulating the approximation in Eq. (1), both thermodynamic influences and convective parameterizations were considered (Emanuel and Zivkovic-Rothman 1999; Kurihara et al. 1998; Pan and Wu 1995); however, other meteorological influences, namely wind shear, were not. As such, Eq. (1) represents the hurricane intensity change only if the tropical system develops. As will be shown below, the simplicity of Eq. (1) makes the evaluation of future hurricane strength probabilities as a function of a given climate scenario straightforward. Thus, Eq. (1) will be used in this study to incorporate future changes in hurricane intensity.

Second, while hurricanes are expected to intensify with global warming, recent studies concluded that the rate of occurrence of hurricanes might change with global warming. In their analysis of the historical record, Webster et al. (2005) concluded that there was no significant change in global tropical cyclone activity between 1970 and 2004. While other studies of the historical record have reported an increase in tropical cyclone activity (Holland and Webster 2007; Mann et al. 2007), Knutson et al. (2010) stated that this observed increase in rate of occurrence is on the same order as the error introduced by limited early capabilities for detecting hurricanes and are thus inconclusive. Bender et al. (2010), by assuming a midrange future climate storyline, A1B (IPCC 2007), presented results from four climate models, with these models predicting a decrease in hurricane rate of occurrence of 8–60% in an 80-year period. On the other hand, model predictions for change in major hurricane (Category 3 and higher) rate of occurrence in this same 80-year period vary from an increase of 40% to a decrease of 60%. By review of a number of tropical cyclone rate of occurrence forecasting studies using dynamical and statistical models (Bengtsson et al. 2007; Gualdi et al. 2008; Oouchi et al. 2006; Zhao et al. 2009), Knutson et al. (2010) concluded that tropical cyclone rate of occurrence will either remain unchanged or decrease somewhat (by 6–34%) with future global warmingby 2100. For this study we will assume a mean rate of change of about −19% per 1°C of SST rise for hurricanes. This approximation is based on climate model projections of Atlantic hurricane rate of occurrence made by assuming a midrange warming A1B storyline (IPCC 2007), which showed an average change of −33% with a 1.72°C SST rise (Bender et al. 2010). This approximation can be written as

$$\lambda_{\Delta SST} = \lambda_o\left[1 - \left(0.19 + \varepsilon_\lambda\right)\left(\Delta SST + \varepsilon_{\Delta SST}\right)\right] \qquad (2)$$

where $\lambda_{\Delta SST}$ = future projected storm rate of occurrence; λ_o = current-day (2000s) storm rate of occurrence; and ε_λ = uncertainty in fractional change in λ_o with ΔSST.

To avoid unrealistically low rate of occurrence projections, if Eq. (2) predicts a value lower than 0.10, $\lambda_{\Delta SST}$ is set to 0.10. In summary, with a long-term global warming trend, eustatic sea levels are expected to rise while hurricanes are expected to intensify but occur somewhat less frequently.

Joint Probability Method Approach for Extreme-Value Flood Statistics

The joint probability method (JPM), first introduced in the 1970s (Ho and Myers 1975; Myers 1975), uses hurricane meteorological probabilities at landfall to assess hurricane forcing probability. When joined with flood response information, the JPM provides a means for developing continuous flood probability density information for extreme-value hurricane flood estimation in a computational efficient manner (JPM-OS) (Resio et al. 2009; Irish et al. 2009). In Irish et al. (2011a), it was demonstrated that the use of JPM-OS for extreme-value surge statistics significantly reduces statistical error, with respect to other popular approaches considering the historical surge population. Although there are a number of statistical approaches available for quantifying tropical cyclone flood statistics (Liu et al. 2009), the JPM-OS has been shown to be highly effective for extreme-value hurricane surge statistics estimation when applied to hurricane-prone locations in the United States (Niedoroda et al. 2010; Resio et al. 2009, 2012). JPM-OS is now the preferred method for U.S. agencies including the U.S. Army Corps of Engineers (2006), the Federal Emergency Management Agency (works in progress), and the U.S. Nuclear Regulatory Commission (2012) for establishing extreme hurricane surge statistics. The application of JPM-OS for hurricane flood statistics requires a model for flood response, z_{max}

$$z_{max}(x) = \phi\left(x, p_o, R_p, v_f, \theta, x_o, \mathrm{MSL}\right) + \varepsilon_z \qquad (3a)$$

$$\varepsilon_z^2 = \varepsilon_{\text{tide}}^2 + \varepsilon_{\text{surge simulation}}^2 + \varepsilon_{\text{waves}}^2 + \varepsilon_{\text{winds}}^2 + \ldots \qquad (3b)$$

where ϕ = continuous flood response function; x = location of interest; x_o = landfall location; R_p = hurricane pressure radius near landfall (Thompson and Cardone 1996); θ = hurricane track angle with respect to the shoreline; v_f = hurricane forward speed near landfall; MSL = mean sea level; and ε_z = epistemic uncertainty in the flood response (Resio et al. 2009, 2012).

Suitable response models in the form of Eq. (3), derived from a high-resolution physics-based numerical simulation of individual hurricane events, have been shown to produce flood elevation estimates with reasonable accuracy while reducing computational requirements by 75% or more (Irish et al. 2009, 2011b). Given known hurricane characteristics, Eq. (3*a*) gives the expected flood response above some prescribed vertical datum. Uncertainty in the estimate of flood response is represented in Eq. (3*b*) and includes uncertainty introduced by numerical simulation error. With the use of Eq. (3), the continuous probability density function (f) can be used to determine the flood return period (T_R)

$$T_R(z_{max}) = \left[1 - \int_{p_o}\int_{R_p}\int_{v_f}\int_{\theta}\int_{x_o} f\left(p_o, R_p, v_f, \theta, x_o\right)\left(H\left\{z_{max} - \left[\phi\left(x, p_o, R_p, v_f, \theta, x_o, \mathrm{MSL}\right) + \varepsilon_z\right]\right\}\right) dx_o\, d\theta\, dv_f\, dR_p\, dp_o\right]^{-1} \qquad (4)$$

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

where H = the Heaviside step function equal to 1 when $z_{\max} - (\phi + \varepsilon_z) \geq 0$ (nonexceedance) and equal to zero (exceedance) otherwise, and f is assumed to be

$$f(p_o, R_p, v_f, \theta, x_o) = \Lambda_1 \Lambda_2 \Lambda_3 \Lambda_4 \Lambda_5 \quad (5a)$$

$$\Lambda_1 = f(p_o|x_o) = \frac{1}{a_1(x_o)} \exp\left[-\frac{\Delta p - a_o(x_o)}{a_1(x_o)}\right] \exp\left\{-\exp\left[-\frac{\Delta p - a_o(x_o)}{a_1(x_o)}\right]\right\} \quad (5b)$$

$$\Lambda_2 = f(R_p|p_o) = \frac{1}{\sigma(\Delta p)\sqrt{2\pi}} \exp\left\{-\frac{\left[\overline{R_p}(\Delta p) - R_p\right]^2}{2\sigma^2(\Delta p)}\right\} \quad (5c)$$

$$\Lambda_3 = f(v_f|\theta) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{\left[\overline{v_f}(\theta) - v_f\right]^2}{2\sigma^2}\right\} \quad (5d)$$

$$\Lambda_4 = f(\theta|x_o) = \frac{1}{\sigma(x_o)\sqrt{2\pi}} \exp\left\{-\frac{\left[\overline{\theta}(x_o) - \theta\right]^2}{2\sigma^2(x_o)}\right\} \quad (5e)$$

$$\Lambda_5 = g(\lambda, x_o) \quad (5f)$$

where Λ_i = the probability density of an individual parameter; a_i = Gumbel coefficients; σ = normal distribution SDs; $g(\lambda, x_o)$ = rate of storm landfall occurrence per unit coastal length; and the overbars denote normal distribution mean values. Eq. (5b) denotes the Gumbel distribution, and Eqs. (5c)–(5e) denote normal distributions.

Uncertainty

An important aspect of understanding and quantifying potential impacts related to climate change is the inherent uncertainty in estimates of future climates. To put such uncertainty into a design and planning perspective, it must be in couched in terms of its magnitude relative to other sources of uncertainty inherent to typical planning and design frameworks. In this section, we give a brief overview of the methods for estimating uncertainties in hurricane flood probabilities given a stationary climate and then investigate additional uncertainties introduced when the climate is allowed to vary systematically.

Typically, uncertainty is separated into two general categories: epistemic (ε_z) and aleatory (ε_a), such that total uncertainty (ε) is

$$\varepsilon^2 = \varepsilon_a^2 + \varepsilon_z^2 \quad (6)$$

The first of these is related to the lack of knowledge in a particular field (e.g., errors due to a lack of understanding the basic physics, numerical assumptions in the surge models, inaccuracies in the wind inputs used to drive the models, and problems with the definition of model grid parameters such as bathymetry, topography, and roughness values). The second of these is related to the inherent uncertainty due to statistical sampling.

Epistemic Uncertainty in Hurricane Flood Estimates

It is difficult to obtain an objective estimate of the error magnitude in surge model estimates for the case of model simulations that are not locally calibrated by observations. For a particular storm, models are usually executed iteratively until all recognized problems are removed from the computational grids, winds, etc., and the model physics have been tuned to provide a relatively accurate fit to observations from that particular storm. However, when one is estimating flood probabilities for designs influenced by hurricanes, it has been shown that it is better to use a modified joint probability method rather than historical storms to estimate the surge design values (Irish et al. 2011a). In this approach the storms used in estimating the flood probabilities are not historical storms, which leads to the question of how much error would be included in these noniteratively simulated storms. For our purpose here, we will assume that the model calibration is sufficiently general, such that all of the model predictions are unbiased. This may not be a valid assumption, but resolving this issue is beyond the scope of the present paper. The SD of the comparisons based on comparisons in the central Gulf of Mexico region, is taken as $\varepsilon_z = 0.7$ m (Resio et al. 2012). There are many additional epistemic factors such as the impact of long-term coastal evolution and the unknown aspects of levee fragility under different types of loading that are neglected in the 0.7-m estimate. If we assume that these are about the same magnitude as our random modeling errors, we end up with a value for epistemic uncertainty of approximately $\varepsilon_z = 1$ m.

Aleatory Uncertainty in Surge Estimates

Two different types of statistical uncertainty contribute to aleatory uncertainty: (1) uncertainty associated with the estimation of the parent population and (2) uncertainty related to the particular storms that might occur during a fixed interval of time. The estimation of uncertainty inherent in the parent population has been extensively studied for the case of known distributions using either parametric (Gringorten 1963) or nonparametric (Efron 1979, 1987; Lee and Young 1995) methods. For comparative purposes, here we will assume that confidence limits can be estimated from a generalized extreme value (GEV) parametric distribution with parameters consistent with the local range of return periods being considered. In this context, uncertainty in the distribution of extreme surges along the unsheltered portions of the central Gulf Coast are estimated to have typical root-mean-square values for the 50-, 100-, and 500-year surge values of $\varepsilon_a = 0.20$, 0.23, and 0.28 m, respectively (Resio et al. 2012). This provides a reasonable estimate of the expected uncertainty in the estimate of the parent population, but does not treat the uncertainty related to the integrated risk of a particular event occurring over a specific time interval. Uncertainty introduced because of uncertainty in future climate conditions additionally contributes to the aleatory uncertainty.

Approach

By considering an idealized coastline, several future carbon emissions storylines, and an extension of the JPM to allow for future changes in climate, we investigate the utility of the JPM for quantification of future extreme hurricane flood statistics and quantification of uncertainty due to uncertainty in future climate conditions.

Climate Storylines

Three IPCC (2007) climate storylines are considered in this analysis:

1. B1: This storyline assumes future use of clean-energy and energy-efficient technologies such that future global carbon emissions are minimized.

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

Table 1. Selected ΔSST and Eustatic SLR *MAGICC/SCENGEN* Climate Projections (Data from Mousavi et al. 2011)

Climate storyline	B1 ΔSST (°C)	A1B ΔSST (°C)	A1FI ΔSST (°C)	B1 eustatic SLR (m)	A1B eustatic SLR (m)	A1FI eustatic SLR (m)
2040s, low estimate	0.60	0.58	0.61	0.10	0.11	0.12
2040s, middle estimate	1.00	1.08	1.20	0.15	0.16	0.17
2040s, high estimate	1.67	1.80	1.99	0.20	0.22	0.23
2080s, low estimate	0.96	1.28	1.64	0.21	0.25	0.30
2080s, middle estimate	1.68	2.20	2.99	0.31	0.37	0.43
2080s, high estimate	2.81	3.80	5.02	0.43	0.51	0.58

Note: Values reported are in reference to conditions in the 2000s.

2. A1B: This storyline assumes a future balanced portfolio of energy sources such that future global carbon emissions are moderated.
3. A1FI: This storyline assumes continued dominance of fossil energy sources such that future global carbon emissions are high.

Potential future ΔSSTand eustatic SLR estimates for the Atlantic basin, based on these three storylines, were interpreted for the 2040s and the 2080s using the climate model *MAGICC/SCENGEN* (*MAGICC/SCENGEN*; J. Smith, Stratus Consulting, personal communication, 2010). For each storyline, three carbon dioxide–doubling sensitivity tests were made at 2, 3, and 4°C by assuming cool, average, and warm conditions (Mousavi et al. 2011). Thus, nine estimates were made per storyline per time period; selected ΔSSTand eustatic SLR estimates are given in Table 1. Model estimates for SST rise rates vary from 0.01 and 0.05°C/year between the 2000s and the 2040s, and between the 2040s and 2080s, SST rise rates vary from 0.01 to 0.08°C/year. Model estimates for eustatic SLR rates vary from 0.25 to 0.58 cm/year and from 0.27 to 0.88 cm/year between the 2000s and 2040s and between the 2040s and 2080s, respectively. In these SLR projections, major ice-sheet melting was not considered. In this analysis, local contributions to future sea-level change, e.g., subsidence, will not be considered.

Joint Probability Method with Flood Response Information Implementation

Implementation of the JPM-OS follows that which was presented in Irish et al. (2011a), where an idealized coastline of 2,000 km in length and with a 1:10,000 continental shelf slope, representative of the northern Gulf of Mexico coastline in the vicinity of New Orleans, Louisiana, is assumed. A summary of this implementation is provided here. For this idealized geometry, maximum surge response functions (SRFs) in the form of Eq. (3*a*) were developed (Irish et al. 2009), where maximum surge ($\zeta_{\max}$) is defined as the water level above mean sea level (MSL). On the basis of computational hurricane surge simulations (Irish et al. 2008), SRFs were approximated as a triangular distribution on the following dimensionless parameters:

$$\zeta'_{\max}(x) = \frac{\gamma\zeta_{\max}(x)}{\Delta p} + m(x)\frac{\Delta p}{\Delta p_{\max}} \tag{7a}$$

$$x' = \frac{(x - x_o)}{R_p} - \delta \tag{7b}$$

where $\zeta'_{\max}(x)$ = dimensionless surge; x' = dimensionless alongshore distance from the location of interest to peak surge; γ = specific weight of water; $m(x)$ = location-dependent constant, $\Delta p_{\max}$ = constant maximum possible central pressure deficit based on a maximum possible intensity argument; and δ = average distance between landfall location (x_o) and peak alongshore surge normalized by R_p.

In Eq. (7), changes in the maximum surge due to changes in hurricane forward speed and approach angle are assumed to be small with respect to other factors (Irish et al. 2008). For implementation here, the flood response function is assumed to be the sum of surge and MSL, and will be taken with respect to the vertical datum of current-day MSL ($\mathrm{MSL_o}$)

$$\phi = \zeta_{\max} + \Delta\mathrm{MSL} \tag{8}$$

where ΔMSL = change in MSL resulting from SLR.

To apply the JPM-OS to future climate conditions, three modifications are made. First, the stationary assumption made on the extreme-value distribution of central pressure is relaxed to allow for a slowly varying distribution through time, namely changes in the fit coefficients a_o and a_1 in Eq. (5*b*). Second, the rate of occurrence of hurricane landfall is similarly allowed to slowly vary through time. Third, a probability distribution on future SST is integrated into the probability density function. For implementation here, the JPM-OS is simplified by excluding both forward speed and angle of approach. The resulting calculation of return period is as follows:

$$T_R(z_{\max}) = \left[1 - \int_{\mathrm{SST}}\int_{p_o}\int_{R_p}\int_{x_o} f(\mathrm{SST}, p_o, R_p, x_o)\{H[z_{\max} - (\phi + \varepsilon_z)]\}dx_o\,dR_p\,dp_o\,d\mathrm{SST}\right]^{-1} \tag{9a}$$

$$f(\mathrm{SST}, p_o, R_p, x_o) = \Lambda_{\mathrm{SST}}\Lambda_1\Lambda_2\Lambda_5 \tag{9b}$$

The current-day distributions of p_o and R_p were estimated from an analysis of landfall statistics for historical hurricanes impacting the Gulf of Mexico coastline (see Irish et al. (2011a) for distribution details). Assumed to be uniform alongshore, the distribution on x_o is then a constant; here the current-day mean rate of hurricane landfall along the 2,000-km coastline is taken to be $\lambda_o = 0.36$. The resulting current-day (2000s) flood elevations for the idealized cases are given in Table 2 and Fig. 1.

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

Future distributions are then estimated as follows. All nine SST estimates for a given storyline are assumed to be equally weighted, such that the distribution is uniform: $\Lambda_{SST} = 0.11$. Similarly, since each SLR estimate corresponds directly to one of the nine SST estimates for a given storyline, the probability distribution for SLR [equal to ΔMSL in Eq. (8)] is accounted for by that for the SST. The future distribution of p_o is estimated by modifying the current-day distribution using Eq. (1). The future conditional probability relationship between R_p and p_o is assumed to be identical to that for current-day conditions. Finally, the constant distribution on x_o is estimated by modifying λ_o according to Eq. (2).

Quantification of Uncertainty because of Future Climate Conditions

Uncertainty introduced into flood statistics by uncertainty in future conditions contributes to both aleatory and epistemic uncertainty. Epistemic contributions arise from uncertainty in future changes to the coastal landscape, and such influences are beyond the scope of this paper. Here, total aleatory uncertainty (ε_a) will be defined as

$$\varepsilon_a^2 = \varepsilon_o^2 + \varepsilon_{\text{climate}}^2 \tag{10a}$$

Table 2. Selected Mean Flood Elevation (m, MSL$_o$) Statistics for Current-Day (2000s) Conditions and by Future Storyline, Inclusive of Projected Future Combined Changes in Storm Rate of Occurrence, Storm Intensity, and Sea-Level Rise

		B1		A1B		A1FI	
T_R (year)	2000s	2040s	2080s	2040s	2080s	2040s	2080s
50	4.49	4.61	4.64	4.62	4.45	4.62	3.84
100	4.88	5.11	5.25	5.12	5.22	5.13	5.06
500	5.54	5.84	6.07	5.86	6.14	5.88	6.20

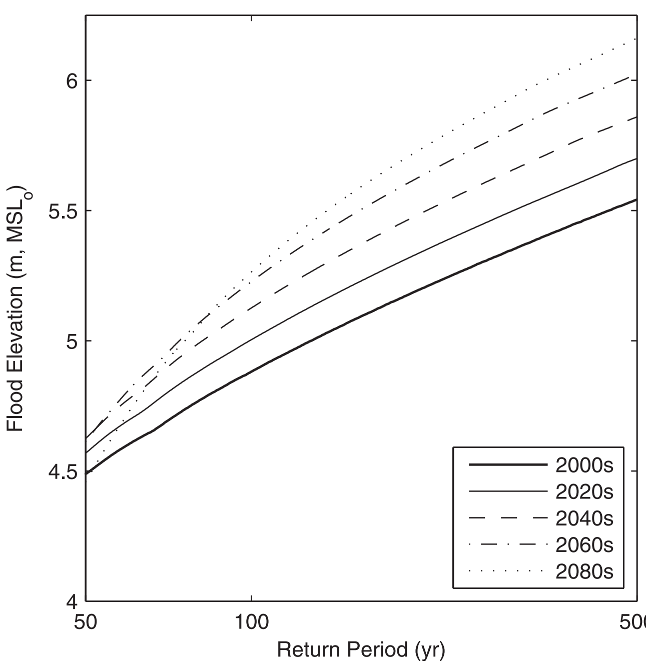

Fig. 1. Future mean flood elevation versus return period for A1B storyline, inclusive of projected future combined changes in storm frequency, storm intensity, and sea-level rise

where

$$\varepsilon_{\text{climate}}^2 = \varepsilon_{\Delta\text{SST}}^2 + \varepsilon_p^2 + \varepsilon_\lambda^2 + \varepsilon_{\text{SLR}}^2 + \dots \tag{10b}$$

where ε_o = current-day (2000s) aleatory uncertainty; and ε_{SLR} = uncertainty in the SLR estimate, given a specified ΔSST.

Here, $\varepsilon_{\text{climate}}$ for a given storyline will be taken to be the SD of all statistical flood elevation estimates at each return period for the nine subscenarios. For the idealized case considered here, ε_o is quantified by assuming a generalized extreme value fit to the current-day (2000s) flood elevation distribution and then estimating the expected root-mean-square error at each return period following Gringorten (1963) (Resio et al. 2009, 2012). This uncertainty for the idealized case is $\varepsilon_o = 0.45, 0.52$, and 0.60 m for $T_R = 50, 100$, and 500 years, respectively.

Results

Projected mean flood statistics by storyline (B1, A1B, and A1FI) for $T_R = 50, 100$, and 500 years are given in Table 2 for the decades of the 2040s and 2080s. By the 2040s, flood elevations are projected to increase between 3 and 6%, depending on return period. Projections for the 2040s by storyline are remarkably similar, with differences of no more than 0.03 m between storylines. In contrast, projected flood elevations for the 2080s do vary by storyline. For B1, an increase in flood elevation, between 3 and 9%, is projected for all return periods. However, for A1B and A1FI these projections show a decrease in flood elevation for lower return periods, yielding changes of −1 and −14%, respectively. For return periods of 100 years or more, an increase in flood elevation is predicted by the 2080s for both the A1B and the A1FI storylines, between 4 and 12% depending on storyline and return period. At the 500-year return period, with respect to current conditions, flood elevations are projected to increase by 0.44, 0.50, and 0.51 m for the B1, A1B, and A1FI storylines, respectively. Estimated aleatory uncertainty, between $\varepsilon_a = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta\text{SST}}^2 + \varepsilon_p^2 + \varepsilon_\lambda^2 + \varepsilon_{\text{SLR}}^2} = 0.46$ and 0.61 m for all storylines, is effectively unchanged for the 2040s projections, changing no more than 4% with respect to the current-day aleatory uncertainty. On the other hand, aleatory uncertainty increases measurably for the 2080s projections to values between $\varepsilon_a = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta\text{SST}}^2 + \varepsilon_p^2 + \varepsilon_\lambda^2 + \varepsilon_{\text{SLR}}^2} = 0.50$ and 1.17 m, with the largest increases associated with the A1FI storyline.

Relative Contributions from Future Hurricane-Climate and Sea-Level Change

The reason the 2080s results exhibit different trends for low and high return periods arises from the relative importance of decreased storm rate of occurrence, increased storm intensity, and SLR. Table 3 presents flood elevation statistics for the A1B storyline when rate

Table 3. Selected Mean Flood Elevation (m, MSL$_o$) Statistics for the A1B Storyline when Projected Future Changes in Storm Rate of Occurrence, Storm Intensity, and Sea-Level Rise Are Considered Separately

		Rate of occurrence only		Intensity only		SLR only	
T_R (year)	2000s	2040s	2080s	2040s	2080s	2040s	2080s
50	4.49	4.31	3.94	4.66	4.83	4.65	4.86
100	4.88	4.76	4.54	5.10	5.32	5.04	5.26
500	5.54	5.46	5.32	5.79	6.04	5.71	5.92

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

of occurrence, intensity, and SLR are considered separately. A decrease in storm rate of occurrence results in reduced flood elevations at all return periods; however, the highest amount of reduction is realized at the lowest return periods. For the 2040s and 2080s, projected decreasing rate of occurrence reduces flood elevations by −2 to −4% and −4 to −12%, respectively. On the other hand, projected increasing storm intensity increases flood elevations by 4–5% and 8–9% by the 2040s and 2080s, respectively. These two competing processes effectively steepen the flood elevation versus return period relationship, supporting the conclusion gleaned from the climatology literature that while storms occur less frequently, the ones that do occur will be more severe. Studying the impact of rate of occurrence and intensity separately reveals that the vast majority of the future climate contribution to aleatory uncertainty arises from changes in rate of occurrence, with changes in intensity contributing no more than $\varepsilon_a - \varepsilon_o = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta SST}^2 + \varepsilon_p^2} - \varepsilon_o = 0.02$ m for any storyline and time period.

By considering the projected added contributions to flood elevation by hurricane intensification and SLR separately, it can be seen that both act to increase flood elevation by roughly the same amount. Projected SLR results in a flood-elevation increase of 3–4% and 7 –8% for the 2040s and 2080s, respectively. Projected intensification results similarly increase flood elevation by 4–5% and 8–9% for the 2040s and 2080s, respectively. The SLR contribution to aleatory uncertainty is negligible, contributing less than $\varepsilon_a - \varepsilon_o = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta SST}^2 + \varepsilon_{SLR}^2} - \varepsilon_o = 0.01$ m. Even if future SLR is substantially larger than what is considered here, e.g., 1 m over the next century, the contribution to aleatory uncertainty remains small. This can be demonstrated by assuming doubled SLR values and repeating the statistical analysis. While mean flood elevations rise linearly with the doubled SLR projections, the SLR contribution to aleatory uncertainty is no more than $\varepsilon_a - \varepsilon_o = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta SST}^2 + \varepsilon_{SLR}^2} - \varepsilon_o = 0.03$ m for any storyline and time period.

Discussion

Error in Mean Trends

The results discussed previously showed that flood elevation statistics are sensitive to changes in hurricane intensity and rate-of-occurrence. Here we explore how sensitive these statistics are to each of these parameters by assuming alternate future mean trend conditions. Bender et al. (2010) reported a range of model projections for future hurricane rate of occurrence; of these, an estimated 23% increase in major hurricane rate of occurrence per 1°C of SST rise can be considered the most extreme case from a flooding perspective. With this assumption, Eq. (2) becomes

$$\lambda_{\Delta SST} = \lambda_o[1 + (0.23 + \varepsilon_\lambda)(\Delta SST + \varepsilon_{\Delta SST})] \tag{11}$$

For discussion, storm rate of occurrence given by Eq. (11) will be referred to asextreme rate of occurrence whereas rate of occurrence given by Eq. (2) will be referred to as original rate of occurrence, Similarly, Knutson and Tuleya (2004, 2008) reported a range of future intensifications with ΔSST. For the Atlantic Basin, the most extreme of these cases is roughly double the rate of intensification assumed previously, ~16% per 1°C of SST rise. With this assumption, Eq. (1) becomes

$$p_{\Delta SST} = p_o - \left[(0.16 + \varepsilon_p)(\Delta SST + \varepsilon_{\Delta SST})\right]\Delta p \tag{12}$$

For discussion, storm intensity given by Eq. (12) will be referred to as extreme intensity, whereas intensity given by Eq. (2) will be referred to as original intensity.

Flood statistics assuming the extreme rate of occurrence and intensity are given in Table 4. A doubling of the rate of intensification increases the flood elevation contribution by intensity an additional 50–100% above that for the original intensity case; with respect to the 2000s, flood elevation for the extreme intensity case increases by 12–16% by the 2080s. The intensity contribution by aleatory uncertainty marginally increases; the 2080s A1B storyline yields a total aleatory uncertainty in the range of $\varepsilon_a = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta SST}^2 + \varepsilon_p^2} = 0.6$ m or less (this equation considers future intensification only). As expected, reversing the trend on future storm rate of occurrence, such that the rate of occurrence increases with ΔSST, yields higher flood elevations under future conditions. Flood contributions by rate of occurrence for the extreme case increases flood elevations by 3–6% by the 2080s. This sensitivity analysis suggests that the mean flood elevation statistics are much more sensitive to the dependencies between global warming and hurricane climate than they are to the assumed global warming trend, i.e., the climate storyline selection.

The extreme rate of occurrence assumption also markedly reduces the rate of occurrence contribution to the aleatory uncertainty to less than $\varepsilon_a - \varepsilon_o = \sqrt{\varepsilon_o^2 + \varepsilon_{\Delta SST}^2 + \varepsilon_\lambda^2} - \varepsilon_o = 0.01$ m. The results of this sensitivity analysis suggest that uncertainty in climate projections, namely the expected mean trends, may have a much larger influence on the flood statistics uncertainty than is indicated by the values reported here.

Adaptive Approaches to Sea-Level Rise

The potential consequences of SLR in coastal regions not only include surge inundation, but also accelerated shoreline erosion, barrier island degradation and break up, changes in coastal bathymetry, loss of wetlands and other coastal habitat, and anthropogenic activities to protect coastal communities, among others. These additional impacts of SLR cause a change in both regional and local surge dynamics. For example, in the case of future barrier island degradation, Irish et al. (2010) showed that when a degraded barrier island system is assumed, flood elevations increase by as much as 0.3 m in Corpus Christi, Texas during moderate hurricane flooding events. The relative role of coastal wetlands on the surge response is complex; for example, Wamsley et al. (2010) concluded that while the loss of wetlands can potentially increase the flooding hazard, the exact amount of additional flooding depends on specific storm

Table 4. Selected Mean Flood Elevation (m, MSL_o) Statistics for the A1B Storyline Using Alternate Extreme Changes in Storm Rate of Occurrence and Intensity

		Extreme rate of occurrence only		Extreme intensity only		Combined extreme rate of occurrence, original intensity, and SLR		Combined original rate of occurrence, extreme intensity, and SLR	
T_R (year)	2000s	2040s	2080s	2040s	2080s	2040s	2080s	2040s	2080s
50	4.49	4.63	4.76	4.81	5.02	5.00	5.56	4.73	4.43
100	4.88	4.99	5.09	5.29	5.62	5.39	5.94	5.30	5.43
500	5.54	5.63	5.70	6.01	6.41	6.04	6.57	6.08	6.48

J. Waterway, Port, Coastal, Ocean Eng. 2013.139:126-134.

conditions and regional coastal landscape configuration. Although quantification of future flood elevation statistics and the associated contribution to epistemic uncertainty in response to major changes in the coastal landscape is beyond the scope of this paper, we explore the implementation of adaptive management approaches as a means to optimize future coastal planning and design.

Considering only the impact of future SLR on flood statistics and considering the A1B storyline, flood elevation statistics were recalculated by making the following assumptions: the lowest SLR subscenario projection is assumed to occur (Column A in Table 5) and the highest SLR subscenario projection is assumed to occur (Column B in Table 5). For both assumptions, it is assumed that the flood statistics are reevaluated every 20 years. In other words, no future projection is extrapolated beyond existing conditions by more than 20 years. For example, for the lowest subscenario SLR projection is assumed to occur up until the 2060s, then the 2080s projection is made by extrapolating from the 2060s baseline using mean rates of change for each subscenario. The resulting mean flood elevation statistics for A and B are shown in Table 5; Fig. 2 shows mean flood elevations for (B). While the mean statistics for A and B for the 2040s vary by only 0.05 m for all return periods, the mean statistics for the 2080s vary by 0.18 m. Shifts in mean flood elevation on the order of 0.15 m can dramatically impact economic assessment of flood damages. More importantly, however, SLR on the order of 0.15 m or more can have a significant impact on the coastal landscape and on coastal development. The implications of planning far ahead and assuming larger rates of SLR is that coastal defenses may be overdesigned and unnecessary costs may be incurred. On the other hand, planning far ahead and assuming low rates of SLR may expose coastal communities to higher flood elevations more often, leading to more casualties, damage, and economic losses when future hurricanes occur.

This analysis suggests that adaptive management approaches are the most viable for optimizing future coastal planning and design initiatives, specifically because the variance in projected SLR can be significantly reduced by forecasting a shorter distance into the future. New coastal defenses can be designed based on short-range projections, but they need to be designed in such a manner to allow for future modification should such modifications be justified.

Conclusions

The statistical method proposed here, namely the use of flood response functions within a joint probability framework, provides an efficient and effective means for assessing future hurricane flood probabilities. In the application of the JPM-OS to an idealized coast, several conclusions can be made with regard to future hurricane flooding. First, given future global warming, hurricane flooding is expected to increase in response to both SLR and a changing hurricane climate. At the 500-year return period, for example, the flood elevation is projected to rise 1% per decade when a simple model for hurricane intensity and rate of occurrence dependency on ΔSST is assumed and mean hurricane climate trends are used. With shorter-range projections on the order of four decades, the flood statistics are minimally impacted by the exact climate storyline selected.

However, this trend of increased flooding more than doubles, yielding a 2–3% increase per decade at the 500-year return period, if alternate mean hurricane climate trends are considered. This leads to a second conclusion that future mean flood statistics are more sensitive to the relationship between the future hurricane climate, namely intensity and rate of occurrence, and the future SST, than they are to the exact climate storyline considered.

Third, aleatory uncertainties introduced in the flood statistics by uncertainties within a given climate storyline are small with respect to other inherent uncertainty contributions; for example, uncertainties related to the simulation of storm surges and estimating the parent storm population based on the historical record. On the other hand, errors in estimating future mean climate trends could lead to much larger aleatory uncertainties than would be indicated by the analyses here. Further, uncertainty in future changes to the coastal landscape, which impact flood levels, could add substantially to the epistemic uncertainty.

Finally, we showed that implementing adaptive management practices can minimize error in future mean flood statistics. It is recommended that adaptive management practices be adopted not only for future extreme-value flood statistics assessments, but also at all levels of coastal planning and engineering design to optimize coastal protection design performance. Adoption of such practices will benefit from future scientific discoveries and advances in the field of climatology, as well as from knowledge gained through observations made in the coming years.

In summary, a generalized method is proposed for quantifying future flood elevation probabilities and associated uncertainties. In practical application of this methodology, it is recommended that

Table 5. Selected Mean FLood Elevation (m, MSL_o) Statistics for the A1B Storyline when Projections Are Made at 20-Year Increments by Assuming a Specific Subscenario Occurs

		Projections from 2000s only		(A) Low estimate occurs		(B) High estimate occurs	
T_R (year)	2000s	2040s	2080s	2040s	2080s	2040s	2080s
50	4.49	4.65	4.86	4.62	4.77	4.67	4.96
100	4.88	5.04	5.26	5.02	5.17	5.07	5.35
500	5.54	5.71	5.92	5.68	5.83	5.73	6.01

Note: Projected future statistics include only projections of sea-level rise.

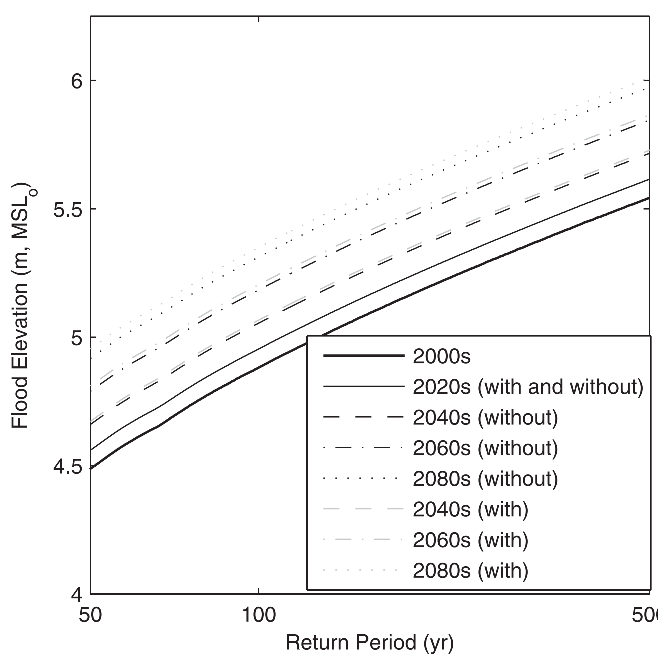

Fig. 2. A1B storyline: future mean flood elevation versus return period where only sea-level rise is considered; black lines are future projections when adaptive management is not considered; gray lines are future projections when adaptive management, at 20-year intervals, is considered and high rate of sea-level rise is assumed to have occurred

a more rigorous formulation of future climate trends be integrated within the probabilistic framework through the consultation of local climate projections.

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Notation

The following symbols are used in this paper:

a_i = Gumbel coefficients;
f = continuous probability density function;
$g(\lambda, x_o)$ = rate of storm landfall occurrence per unit coastal length;
$m(x)$ = location-dependent constant;
p_o = current-day (2000s) hurricane central pressure;
$p_{\Delta\mathrm{SST}}$ = future projected hurricane central pressure;
R_p = hurricane pressure radius near landfall;
T_R = return period;
v_f = hurricane forward speed near landfall;
x = location of interest;
x' = dimensionless alongshore distance from location of interest to peak surge;
x_o = landfall location;
$z_{\max}$ = flood response;
γ = specific weight of water;
Δp = far-field barometric pressure less central pressure;
$\Delta p_{\max}$ = constant maximum possible central pressure deficit based on a maximum possible intensity argument;
δ = average distance between landfall location (x_o) and peak alongshore surge normalized by R_p;
ε = total uncertainty;
ε_a = aleatory uncertainty;
$\varepsilon_{\mathrm{climate}}$ = contribution to aleatory uncertainty due to uncertainty in the future climate;
ε_o = current-day aleatory uncertainty;
ε_p = uncertainty in the fractional change in Δp with ΔSST;
$\varepsilon_{\mathrm{SLR}}$ = uncertainty in the SLR projection;
ε_z = epistemic uncertainty;
$\varepsilon_{\Delta\mathrm{SST}}$ = uncertainty in the ΔSST projection;
ε_λ = uncertainty in fractional change in λ_o with ΔSST;
$\zeta_{\max}$ = maximum surge;
$\zeta'_{\max}(x)$ = dimensionless surge;
θ = hurricane track angle with respect to the shoreline;
Λ_i = probability density of an individual parameter;
λ_o = current-day (2000s) storm rate of occurrence;
$\lambda_{\Delta\mathrm{SST}}$ = future projected storm rate of occurrence;
σ = normal distribution SDs;
ϕ = continuous flood response function; and
overbars = denote normal distribution mean values.

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