



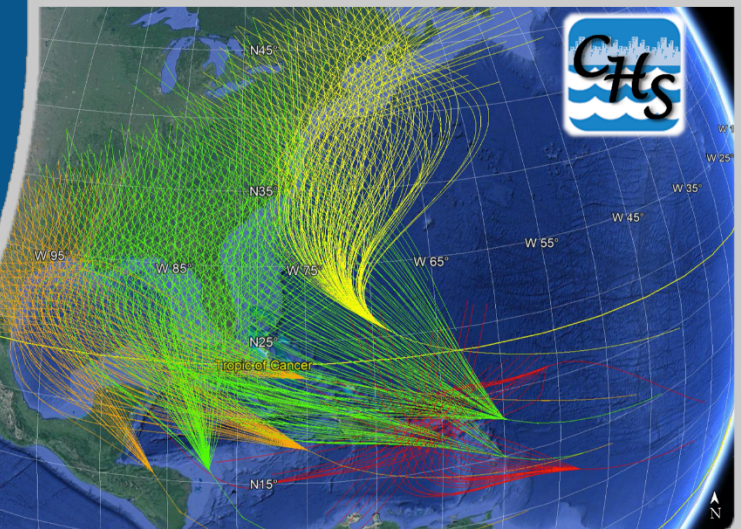
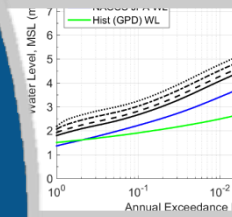
6th Annual Probabilistic Flood Hazard Assessment Research Workshop Rockville, MD

Storm Surge Modeling Uncertainty

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Outline

- **Introduction**
 - TC Joint probability analysis
 - JPM integral error term
- **Methods and Models Assessment**
 - Application of error term.
 - Neglecting error term.
 - Astronomical tide and Holland B error terms.
 - Relative and absolute bias and uncertainty.
 - Spatially varying uncertainty.
- **Summary**

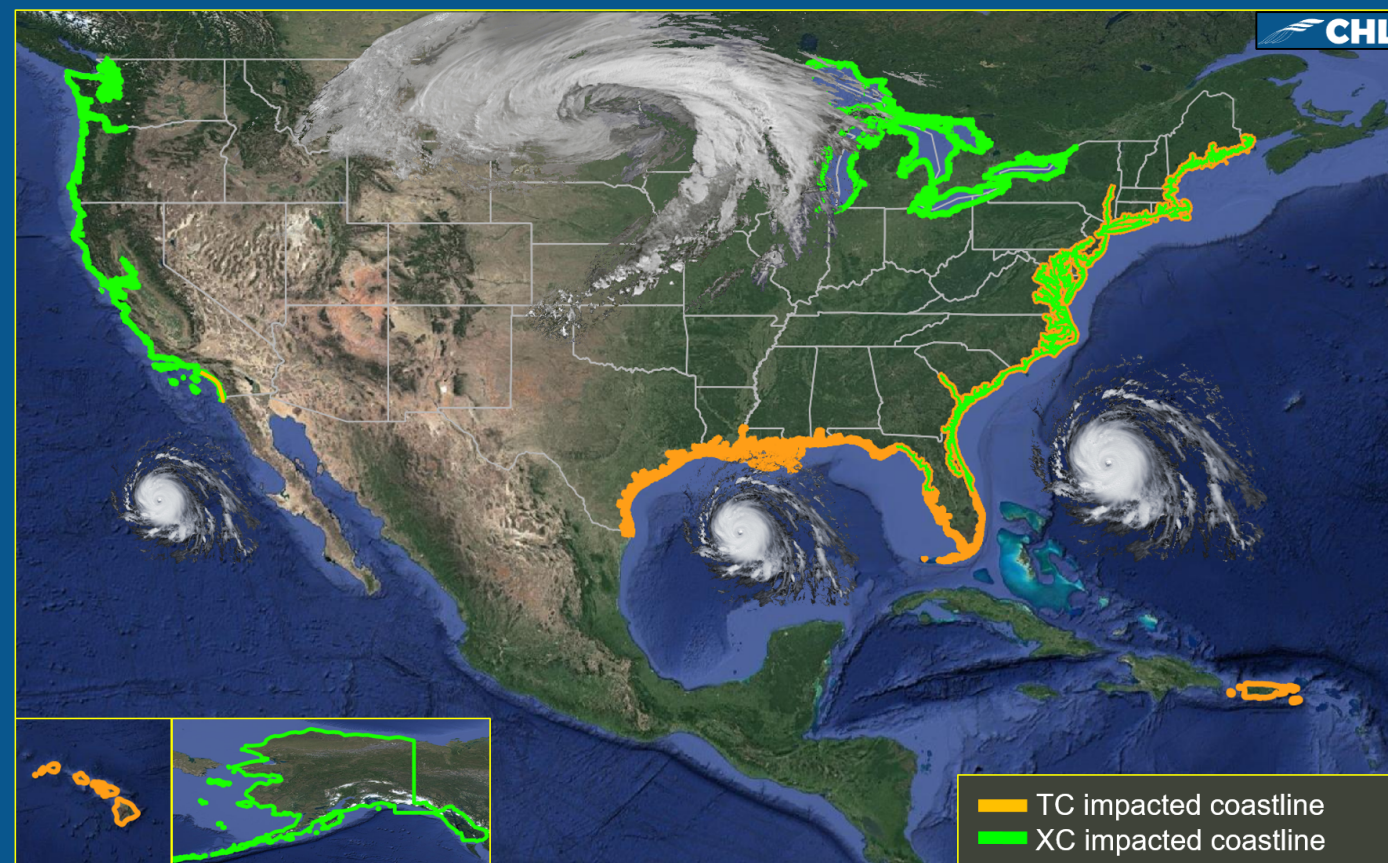
Introduction

- **Main objective: evaluate sources of aleatory and epistemic uncertainty in probabilistic modeling of numerical surge simulation errors.**
- **Work conducted as part of “Quantification of Uncertainties in Probabilistic Storm Surge Models” study within U.S. NRC’s Probabilistic Flood Hazard Assessment (PFHA) research plan.**
- **General approach**
 - **Develop hazard curves with uncertainty represented through confidence limit curves.**
 - **Epistemic uncertainty obtained through the evaluation of alternate data, models, and methods used in probabilistic storm surge models.**
 - **Consider AEPs that go beyond traditional state-of-practice for non-nuclear facilities (e.g., 10^{-4} to 10^{-6}).**



Probabilistic storm surge modeling

- Approach for quantification of coastal storm hazards (e.g. surge) dependent on type of cyclonic exposure.
 - Tropical cyclones (TC).
 - Extratropical cyclones (XC).
- Probabilistic coastal hazard analysis for hurricane exposed coastlines requires → Joint probability analysis of TC forcing parameters.
 - Development of synthetic TCs through sampling joint distribution of TC parameters.
 - Atmospheric modeling of TCs wind and pressure fields and hydrodynamic modeling of water levels and waves.



- **Why JPA approach with synthetic storms?**
 - TC hazard is spatially and temporally underrepresented in historical record.
- **Joint probability method (JPM) is the standard JPA model approach for TCs.**
 - JPM-OS
 - USACE PCHA (Nadal-Caraballo et al. 2020).
- **Standard TC Forcing Parameters.**
 - Track position (reference location, x_0).
 - Track angle (heading direction, θ).
 - Intensity (central pressure deficit, Δp).
 - Size (radius of maximum winds, R_{max}).
 - Translational speed, V_t .
- **TCs with Michael's characteristics can be represented within JPM probability space.**

Joint probability method

JPM Integral

$$\lambda_{r(\hat{x}) > R} = \lambda \int P[r(\hat{x}) + \varepsilon > r | \hat{x}, \varepsilon] f_{\hat{x}}(\hat{x}) f_{\varepsilon}(\varepsilon) d\hat{x} d\varepsilon$$

$$\approx \sum_i^n \lambda_i P[r(\hat{x}) + \varepsilon > r | \hat{x}, \varepsilon]$$

where:

$\lambda_{r(\hat{x}) > R}$ = AEF of TC response R due to forcing vector \hat{x}

$\hat{x} = f(x_o, \theta, \Delta p, R_{max}, V_t)$

λ = SRR (storms/yr/km)

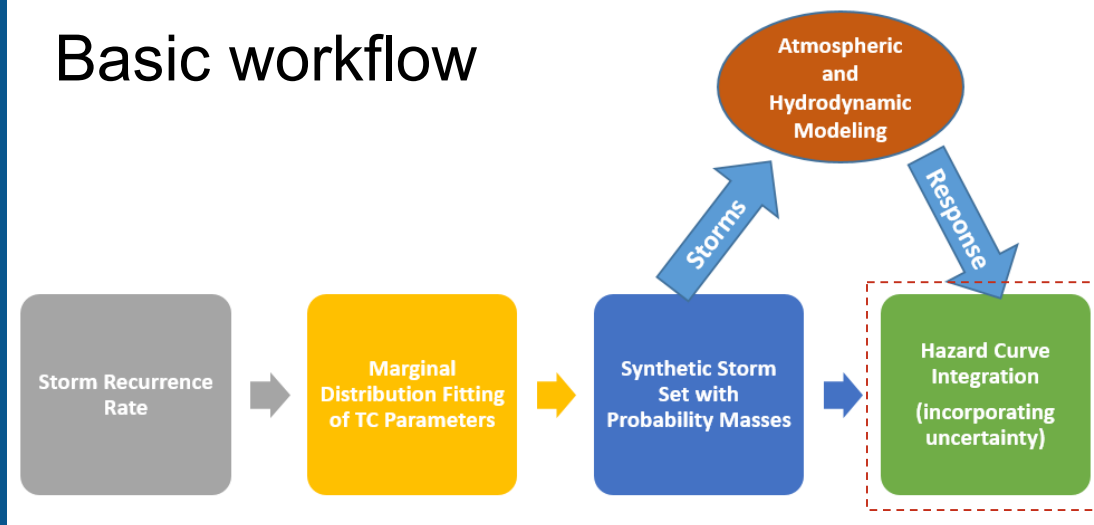
$\hat{\lambda}_i$ = probability mass (storms/yr) or λp_i ,

with p_i = product of discrete probability and TC track spacing (km)

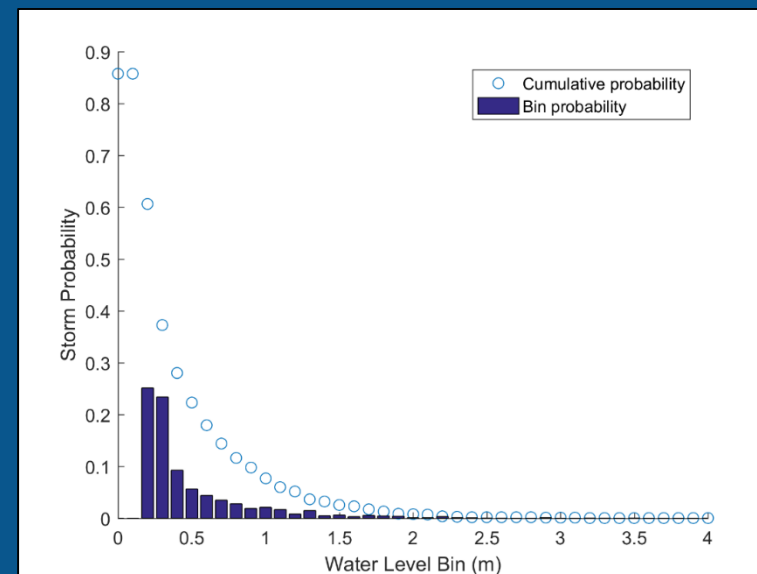
$P[r(\hat{x}) + \varepsilon > r | \hat{x}, \varepsilon]$ conditional probability that storm i with parameters \hat{x}_i generates a response larger than r
 ε = unbiased error or aleatory uncertainty of r



Basic workflow



Probabilities of water level bins and construction of AEF curve.



The error term “ ε ”

- Error term components
 - Hydrodynamic modeling errors.
 - ▶ Unresolved physical processes.
 - ▶ Inadequate resolution/topo bathy errors.
 - Meteorological modeling errors.
 - ▶ Simplified wind and pressure fields representation.
 - Holland B.
 - Tide (Gulf coast)
- Assumption of normality and application of central limit theorem.
 - Combined error represented as a Gaussian distribution with mean zero.
 - Errors are unbiased → If present, **correct bias**.
 - Standard deviation of error, σ_ε , represents uncertainty.

Total bias from summation of individual biases

$$\mu_\varepsilon = \mu_{\varepsilon 1} + \mu_{\varepsilon 2} + \cdots + \mu_{\varepsilon n}$$

where μ_ε = bias (mean of the error).

Total uncertainty

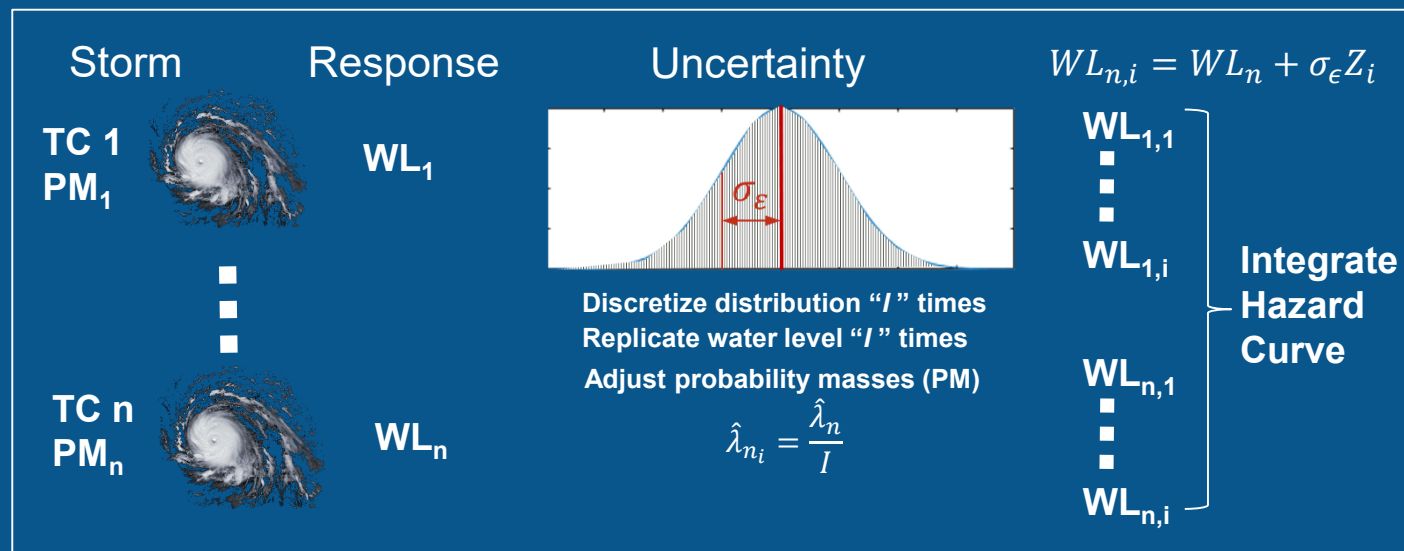
$$\sigma_\varepsilon = \sqrt{\sigma_{\varepsilon 1}^2 + \sigma_{\varepsilon 2}^2 + \cdots + \sigma_{\varepsilon i}^2}$$

Methods and Models Assessment



Application of the error term “ ϵ ”

- Distribution of error inside JPM integral (e.g. FEMA)



- Uncertainty allocation between integral and confidence limits).

$$\sigma_\epsilon = \sqrt{\sigma_{int}^2 + \sigma_{CL}^2}$$

Confident Limit, CL:

$$CL = WL + Z * WL * \sigma_{CL}$$



- Completely within confidence limits.

- Requires a very large number of storms for proper characterization of mean hazard curve.
- No smoothing required.
- Applied in USACE PCHA using augmented storm suite developed with surrogate modeling (Nadal-Caraballo et al. 2020)

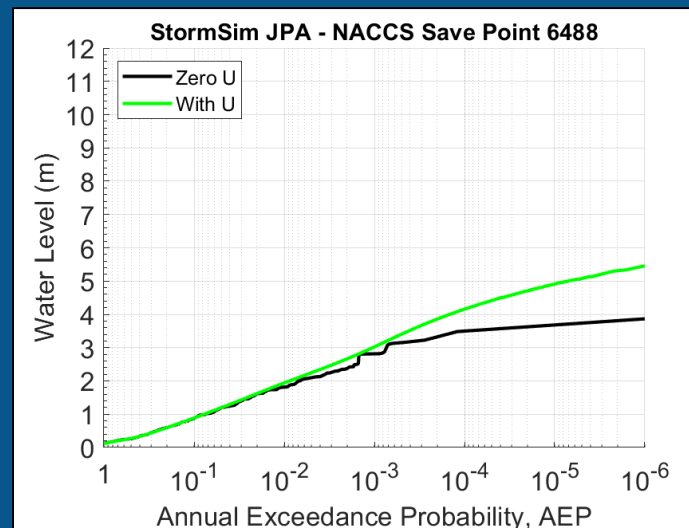
Main limitations

- Inside integral – No confidence limits
- Inside Integral and confidence limit – No consensus allocation.
- Confidence limits only – requires thousands of storms.

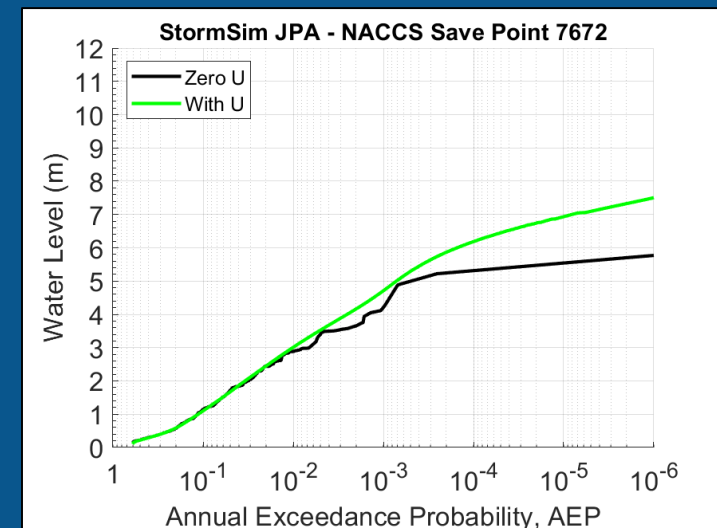
Neglecting the error term

- What are the effects of the non-inclusion of the error term in the integral?
- Underestimation of the hazard.
 - Hazard curves start diverging within the 10^{-2} to 10^{-3} AEP range.
 - Underestimation of 20-30% for 10^{-6} AEP (range of interest to Nuclear Power Plants)
- No smoothing effect in the hazard curve.

Virginia Beach, VA



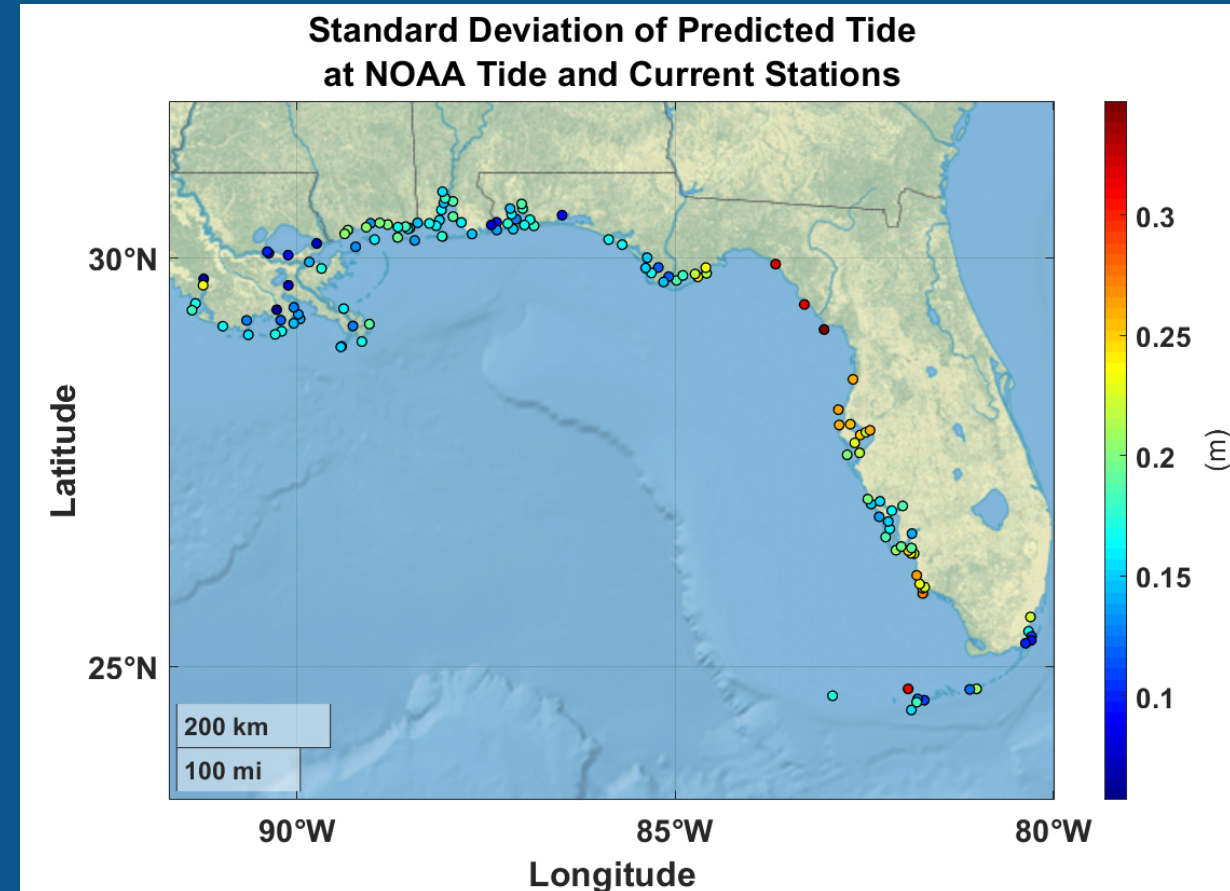
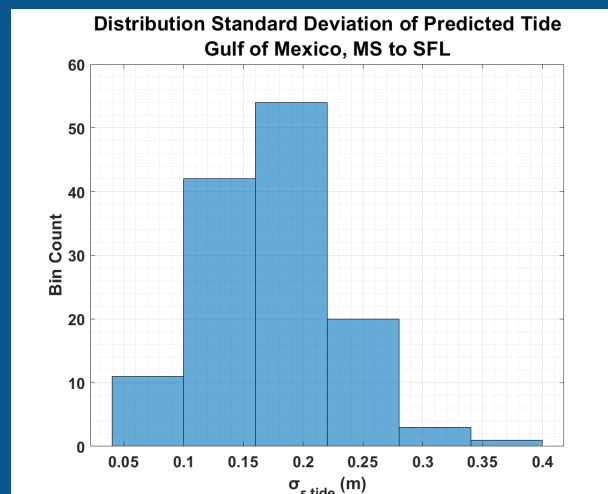
The Battery, NY



Location	Error Term	AEP – Water Levels (m)					
		1×10^{-2}	0.2×10^{-3}	1×10^{-3}	1×10^{-4}	1×10^{-5}	1×10^{-6}
The Battery, NY	Without	1.81	2.37	2.81	3.50	3.68	3.87
	With	1.94	2.67	3.02	4.16	4.91	5.46
	Difference (%)	-6.46	-10.91	-6.89	-15.86	-25.04	-29.16
Virginia Beach, VA	Without	2.88	3.66	4.21	5.31	5.54	5.77
	With	3.01	4.17	4.71	6.18	6.93	7.50
	Difference (%)	-4.23	-12.23	-10.66	-14.08	-20.08	-23.10

Astronomical tide as secondary TC parameter.

- Treated as secondary TC parameter at locations with small tidal range.
- Incorporated statistically within the error term of the JPM equation ($\sigma_{\epsilon tide}$).
- Computed from tide gage data as the deviation from a random tide phase and the zero tide level.

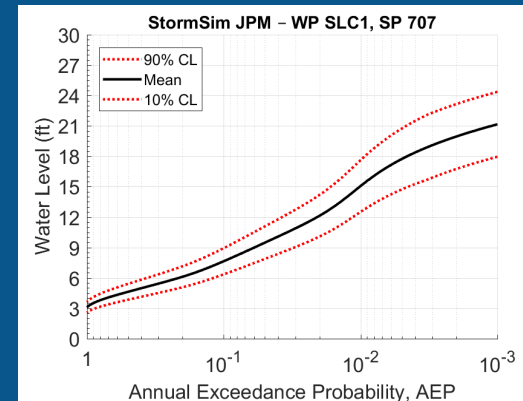


Median SD = 0.17 m
 90% Percentile SD = 0.25 m
 10% Percentile SD = 0.11 m

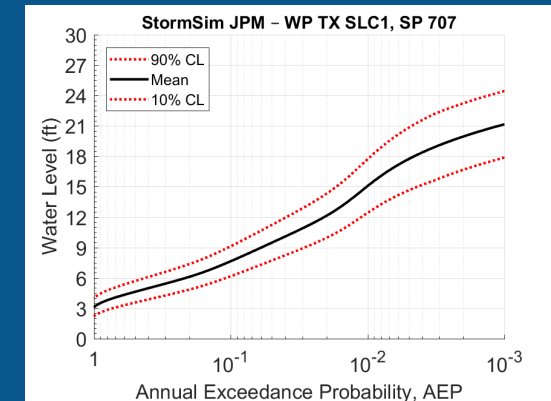
Astronomical tide as secondary TC parameter (cont.)

- Adequacy of incorporating tide as an error term.
- Assessment by Melby et al. (2020) for the Texas Gulf coast.
 - Used synthetic TC and modeling data from Texas Coastal Study (Nadal-Caraballo et al. 2018).
 - Tidal statistics obtained from a 5 year sample from NOAA tide and currents station 877570 Sabine Pass North.
- Compared still water levels hazard curves using three methods:
 - ▶ No tide.
 - ▶ Tide as a statistic (secondary JPM parameter).
 - ▶ Historical tides sampled using Monte Carlo Simulation using linear superposition.
- Tides can be included as statistic.

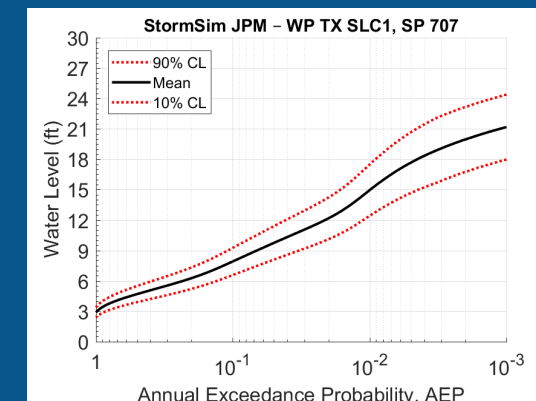
No Tide



Tide as statistic



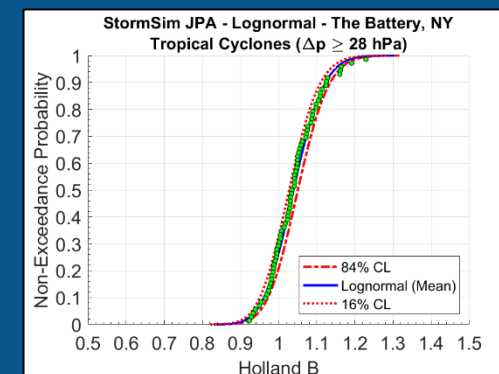
Explicit tide



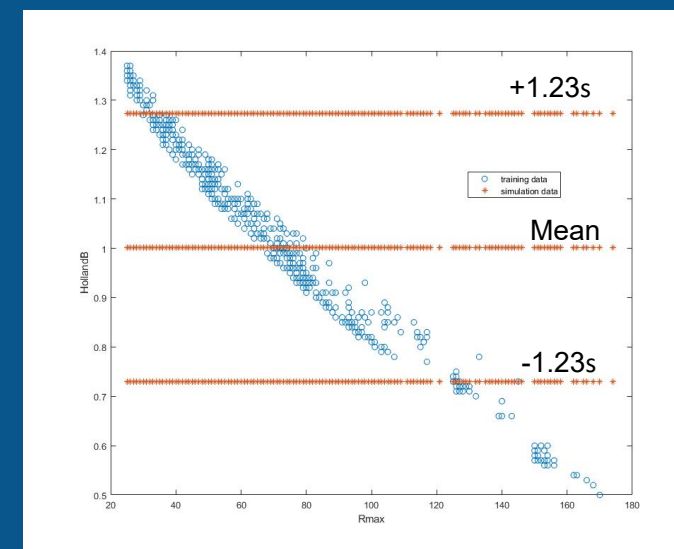
No significant impacts on results

Holland B

- Synthetic TCs wind radial profiles are defined by **Holland B** parameter (Holland 1980).
- The **error term** accounts for the variation of Holland B with respect to the values modeled in the synthetic TCs.
- Approaches for incorporating Holland B.
 - As secondary parameter.
 - ▶ Uniform Holland B values for all TCs with three along track variations used with respect to landfall.
 - ▶ Consideration of Holland B variation using statistical models of the parameter (e.g. Vickery and Wadhera 2008). Holland B is computed individually for each storm.
 - As primary JPM parameter (error term set to zero), estimated with statistical model.
 - ▶ Considerations:
 - Additional parameter discretization increases computational burden.
 - High correlation to R_{max} might limit information gained.
- Holland B might not provide significant additional information. It's an empirical function of Δp , R_{max} and location.



Lognormal marginal distribution fit of Holland B



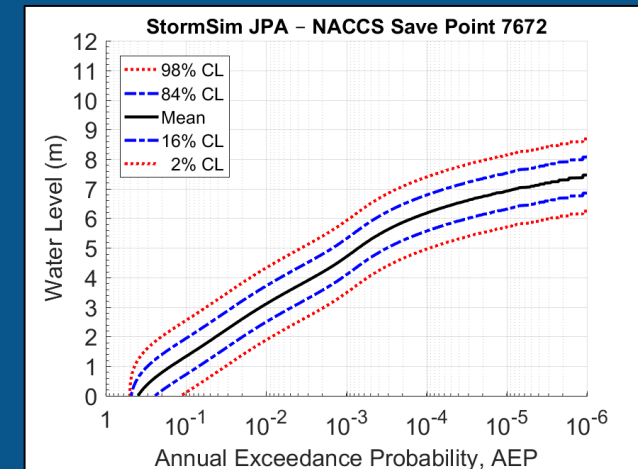
Three discretizations of Holland B

Holland B. Estimated, highly correlated to other parameters, specially R_{max}

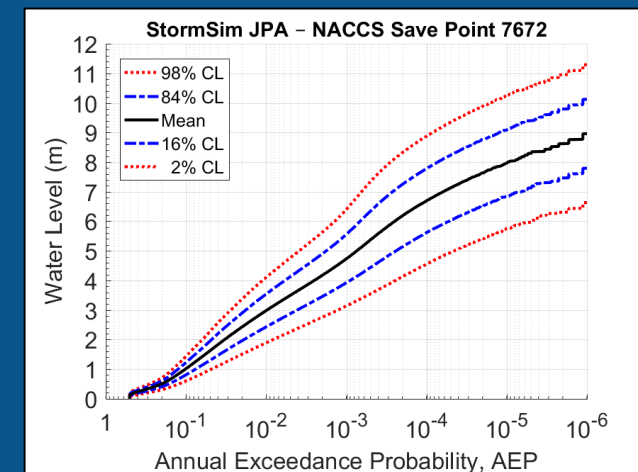
Model bias and uncertainty

- Quantification of model errors are necessary for calibration and validation of model performance.
- Two main components of error relate to accuracy and precision.
 - Systematic error (bias) – mean of the error.
 - Spread (uncertainty) – standard deviation of the error.
- Quantified by comparing model performance with measurements.
- Computed based on high water marks and gage readings.
- Two types can be computed:
 - Absolute bias and uncertainty (dimensional).
 - Relative bias and uncertainty (non-dimensional).
- Issues related to the application of these types of uncertainties.
 - Absolute: for small surge values, the uncertainty could be the same order of magnitude as the surge.
 - Relative: if computation based on small measured values, it could result in unrealistic errors for large values of surge.

Absolute uncertainty



Relative uncertainty



Combination of absolute and relative uncertainty

- Alternatives for combining uncertainty
 - Use absolute uncertainty to constrain the relative uncertainty.

$$\sigma_{constrained} = Z \times \min\{WL * \sigma_{rel}, \sigma_{abs}\}$$

- Combine through the use of weighting factor (w).

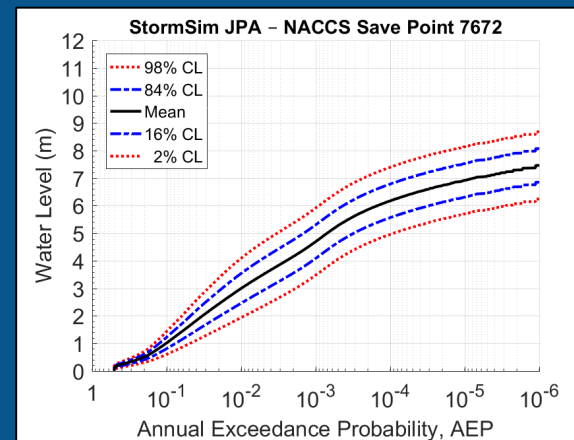
$$\sigma_w = w * Z * \sigma_{abs} + (1 - w) * Z * WL * \sigma_{rel}$$

- Combination approach based on data assimilation error statistic described in Gao et al. (2012).

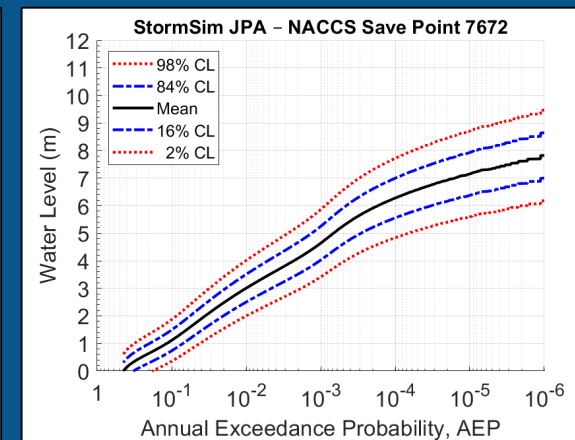
$$c = \frac{1}{\sqrt{\frac{1}{a^2} + \frac{1}{r^2}}}; \quad \text{where } c = \text{combined uncertainty, } a = \text{absolute uncertainty, } r = \text{relative uncertainty}$$



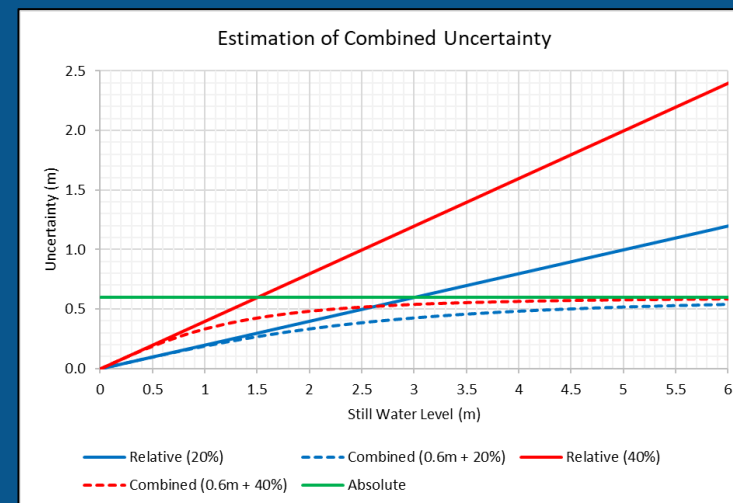
Constrained uncertainty



50% weighting factor



Combined DA approach comparison



Spatially-varying modeling error

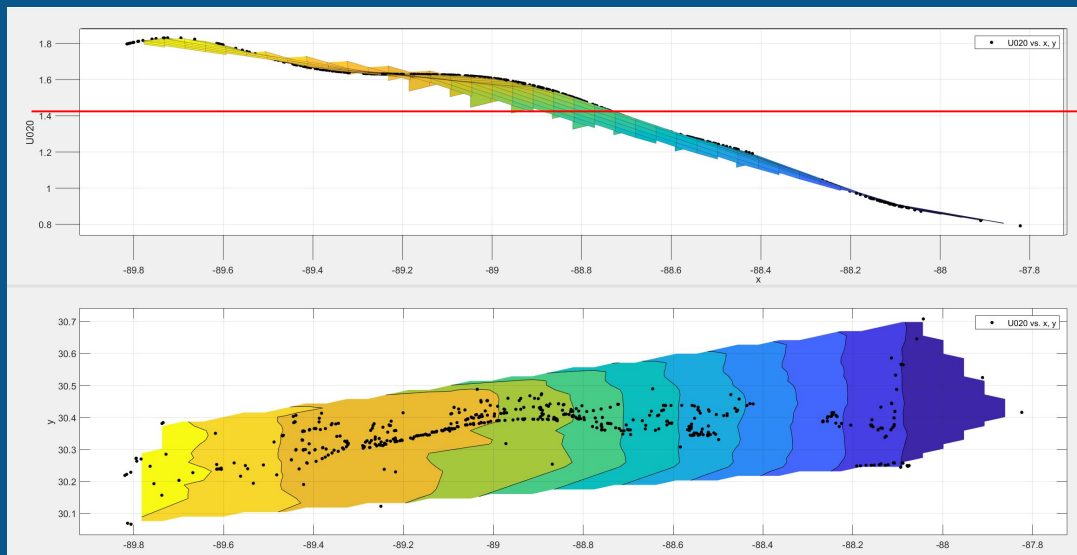
Modeling error: has a direct effect on hazard curve shape and confidence limits.

- Gaussian kernel surface (GKS) approach
- Global uncertainty: 1.42 ft.
- Spatially varying uncertainty:

Method applies Gaussian kernel function (GKF) to obtain distance adjusted weights at a water level measurement location with respect to other water level measurements locations.

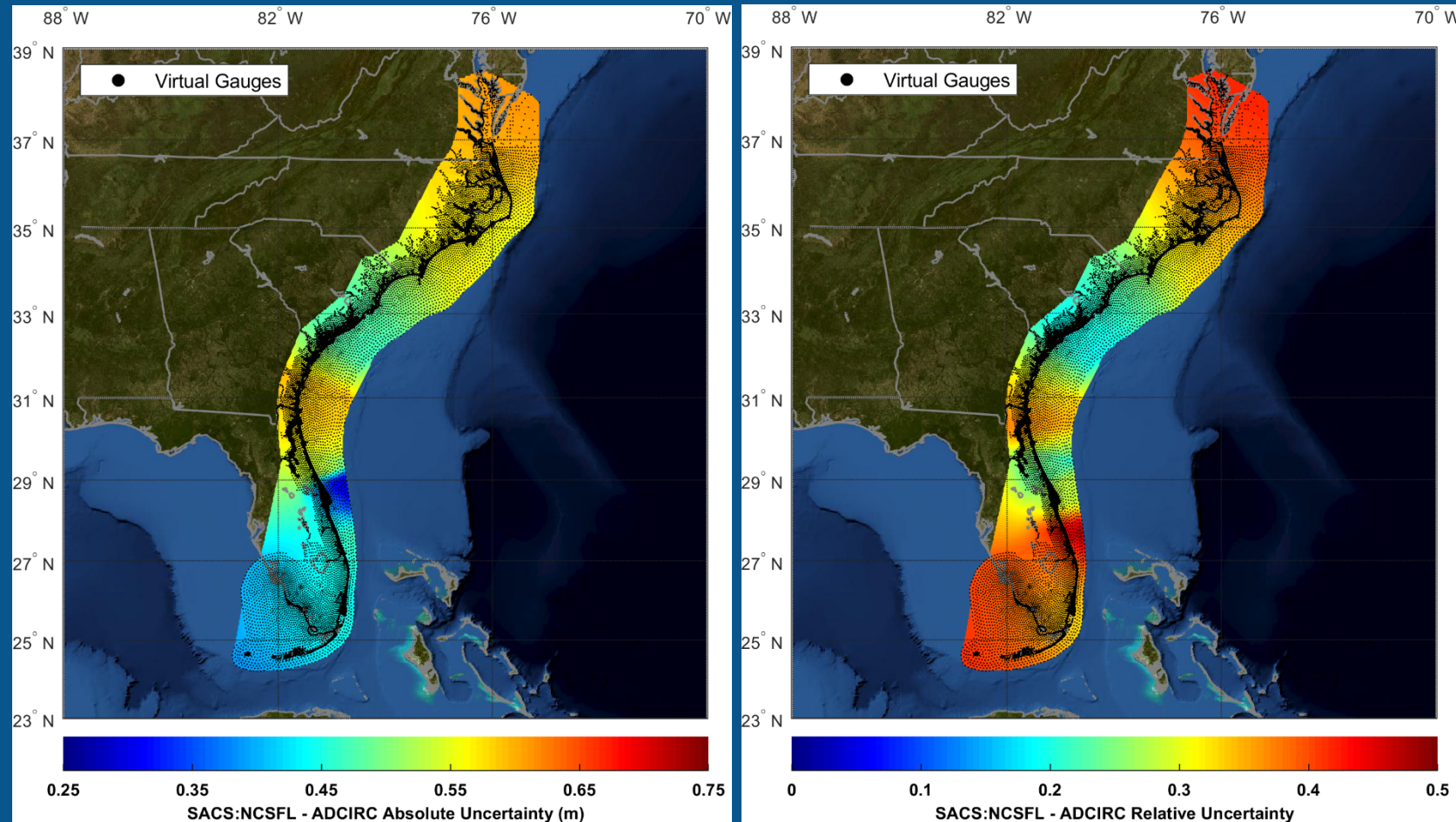
$$w(d_i) = \frac{1}{\sqrt{2\pi}h_d} \exp \left[-\frac{1}{2} \left(\frac{d_i}{h_d} \right)^2 \right]$$

where $w(d_i)$ = distance-adjusted weights from the Gaussian probability density function (PDF); d_i = distance from location of interest to other measurement location points (kilometers); h_d = optimal kernel size (kilometers).



Spatially-Varying relative and absolute uncertainty

- South Atlantic Coastal Study Example (Nadal-Caraballo et al. 2021)



Numerical Model	Average Uncertainty	
	Absolute (m)	Relative
ADCIRC	0.4998	0.3119
PBL	0.2027	0.2683
Total (ADCIRC & PBL)	0.5420	0.4148
Numerical Model	Absolute (m)	Relative
STWAVE (H_{m0})	1.512	0.3126

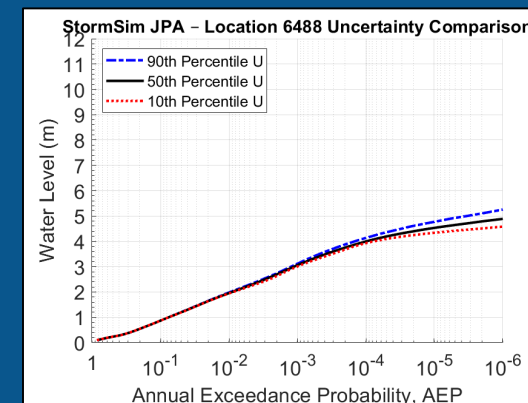
Impact of spatial variation of model error

- Spatially-varying hydrodynamic model uncertainty was computed for the North Atlantic Coast Comprehensive Study.
- Effect on hazard tested by comparing 10th 50th and 90th percentile errors.
- Combined uncertainty using constrained approach.
- The difference between 10th and 90th percentile uncertainty values small.
- Impact observed at very low AEPs.

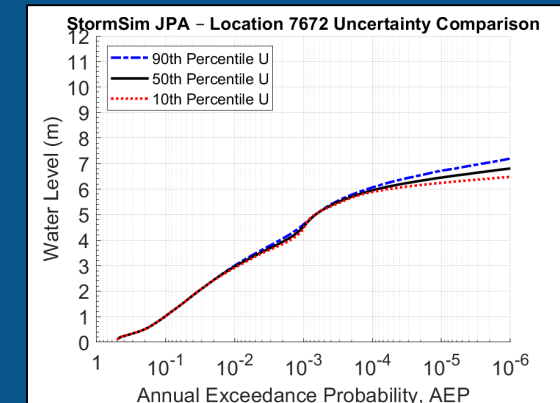
Select statistics for spatially varying model uncertainty

Statistic	Uncertainty (m)	Relative Uncertainty
Mean	0.36	0.16
Median	0.34	0.16
90 th percentile	0.50	0.19
10 th percentile	0.24	0.13

Virginia Beach, VA



The Battery, NY

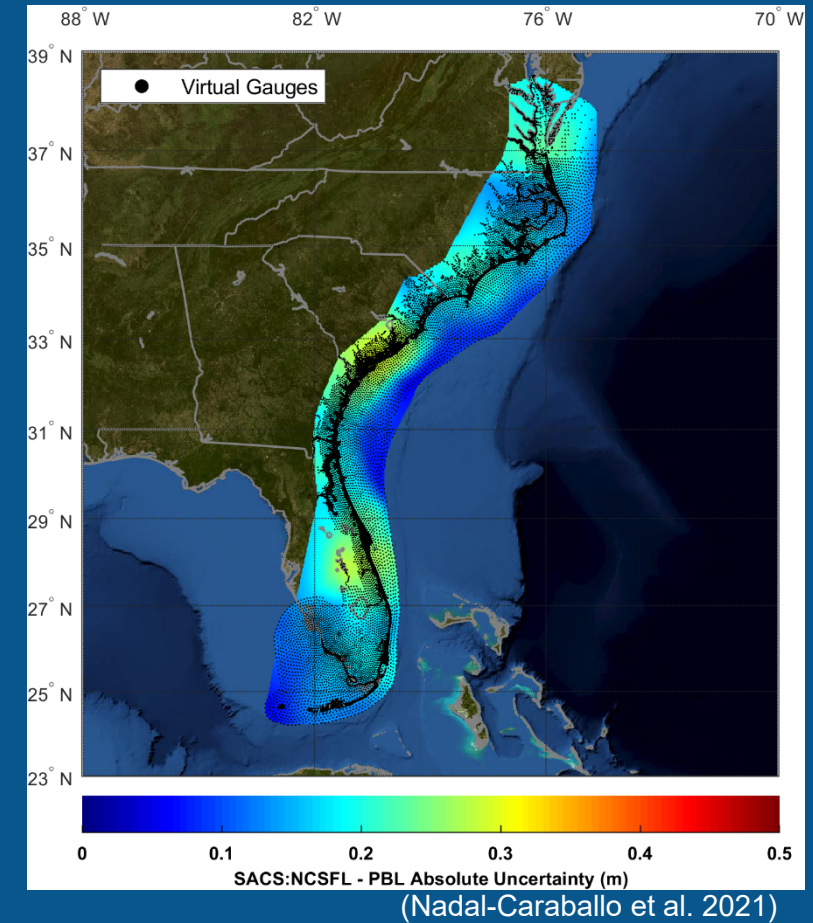
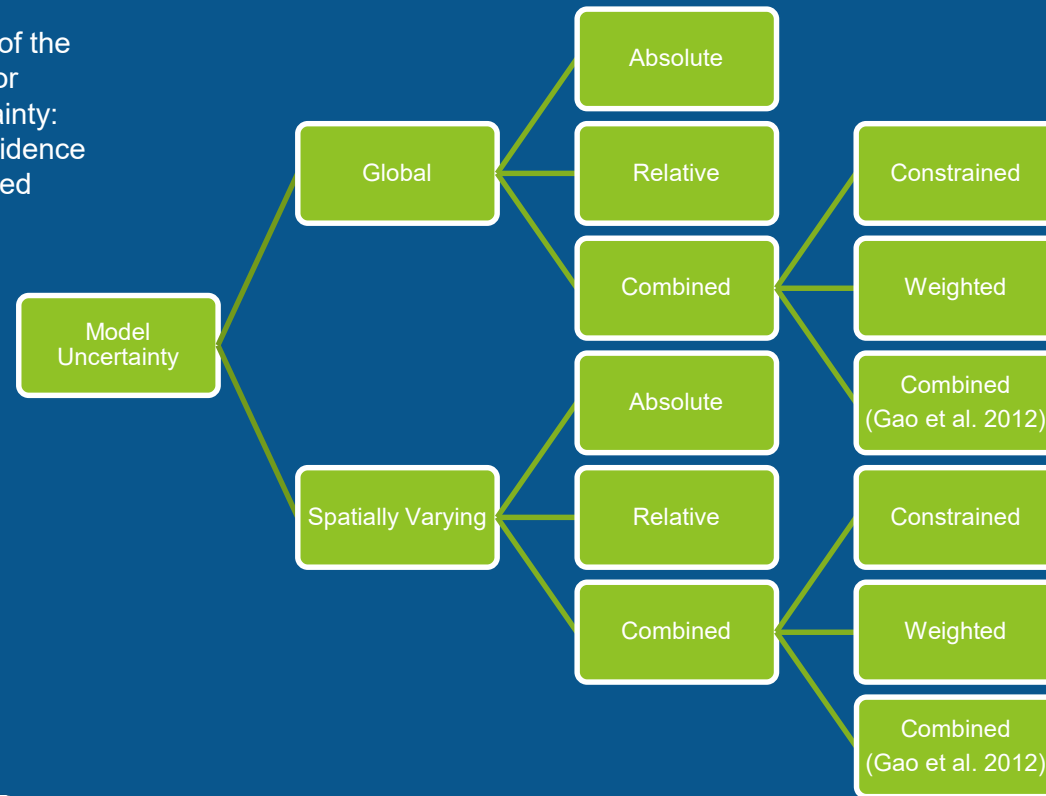


Location	Applied uncertainty statistics	AEP - Water Levels (m)					
		1X10 ⁻²	0.2X10 ⁻³	1X10 ⁻³	1X10 ⁻⁴	1X10 ⁻⁵	1X10 ⁻⁶
The Battery, NY	90 th	2.99	4.06	4.61	6.07	6.72	7.19
	Median	2.96	3.93	4.53	5.95	6.45	6.81
	10 th	2.91	3.84	4.45	5.89	6.25	6.48
	Difference (%)	2.8	5.5	3.5	3.0	7.3	10.5
Virginia Beach, VA	90 th	1.96	2.70	3.06	4.00	4.53	4.89
	Median	1.96	2.70	3.06	4.00	4.53	4.89
	10 th	1.94	2.63	3.01	3.93	4.34	4.58
	Difference (%)	0.7	2.5	1.6	1.6	4.3	6.3

Probabilistic surge modeling uncertainty branches

- Multiple paths can be used to compute meteorological and hydrodynamic modeling uncertainty.

Applies to each of the three methods for applying uncertainty: To integral, confidence limit, and allocated between both.



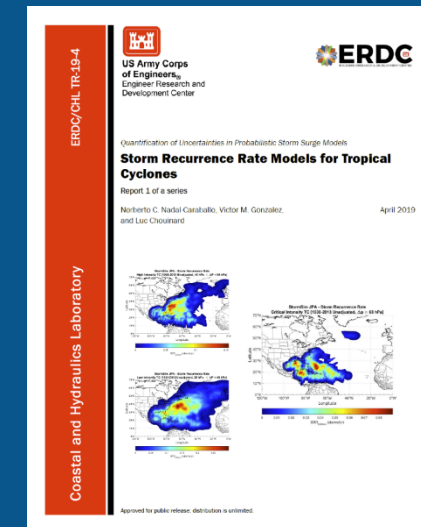
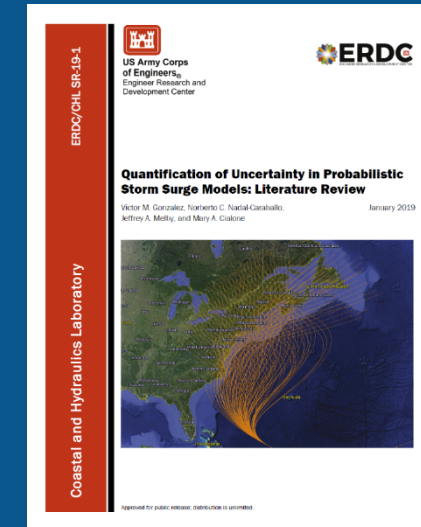
Summary

- Several approaches for characterizing and modeling of errors storm surge modeling were evaluated.
- Aleatory uncertainty in probabilistic storm surge modeling accounted for in “error” term of JPM integral.
- Epistemic uncertainty can be characterized from the consideration of these approaches:
 - Manner of incorporating uncertainty in JPM integral.
 - Characterization of bias and uncertainty.
 - Consideration or not of spatially-varying uncertainty.
- Use of absolute and relative uncertainties, as well methods for combining them, have a significant impact on the computed hazard.
- Availability of measured water level data has a significant impact on the quantification of the numerical modeling bias uncertainty. Historic measurement data is typically limited in terms of quantity and quality.
- Spatially-varying bias and uncertainty has an effect in the quantification of the hazard compared with use of global uncertainty, in particular for smaller AEPs.



Reports

- Gonzalez V.M., N.C. Nadal-Caraballo, J.A. Melby, and M.A. Cialone. 2019. *Quantification of Uncertainty in Probabilistic Storm Surge Models: Literature Review*. ERDC/CHL SR-19-1.
- Nadal-Caraballo, N.C., V.M. Gonzalez, and L. Chouinard. 2019. *Quantification of Uncertainties in Probabilistic Storm Surge Models: Storm Recurrence Rate Models for Tropical Cyclones*, ERDC-CHL TR-19-4. Vicksburg, MS: U.S. Army Engineer Research and Development Center.
- Nadal-Caraballo, N.C., V.M. Gonzalez, E. Ramos-Santiago, and M.O. Campbell. *Data, Models, and Methods for Defining Joint Probability of Storm Parameters and Generating Synthetic Storm Simulation Sets*. ERDC/CHL TR-20-X (In Review)



References

- Gao, F., X. Zhang, N. A. Jacobs, X.-Y. Huang, X. Zhang, and P. P. Childs. 1972. Estimation of TAMDAR Observational Error and Assimilation Experiments. *Weather and Forecasting* 27:856-877.
- Nadal-Caraballo, N. C., M. O. Campbell, V. Gonzalez, M. J. Torres, J. A. Melby, and A. A. Taflanidis. 2020. Coastal Hazards System: A Probabilistic Coastal Hazard Analysis Framework. Proceedings from the International Coastal Symposium (ICS) 2020. *Journal of Coastal Research* 95:1211-1216.
- Nadal-Caraballo, N.C., M.O. Campbell, M.L. Carr, E. Ramos-Santiago, V.M. Gonzalez, M.J. Torres, A.A Taflanidis, and A.T. Cox. 2021. Coastal Hazards System: South Atlantic Coast Study – North Carolina to South Florida. ERDC/CHL TR-21-XX. Vicksburg, MS: U.S. Army Engineer Research and Development Center.
- Vickery, P.J., and D. Wadhera. 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.



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