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ERDC
Engineer Research and Development Center

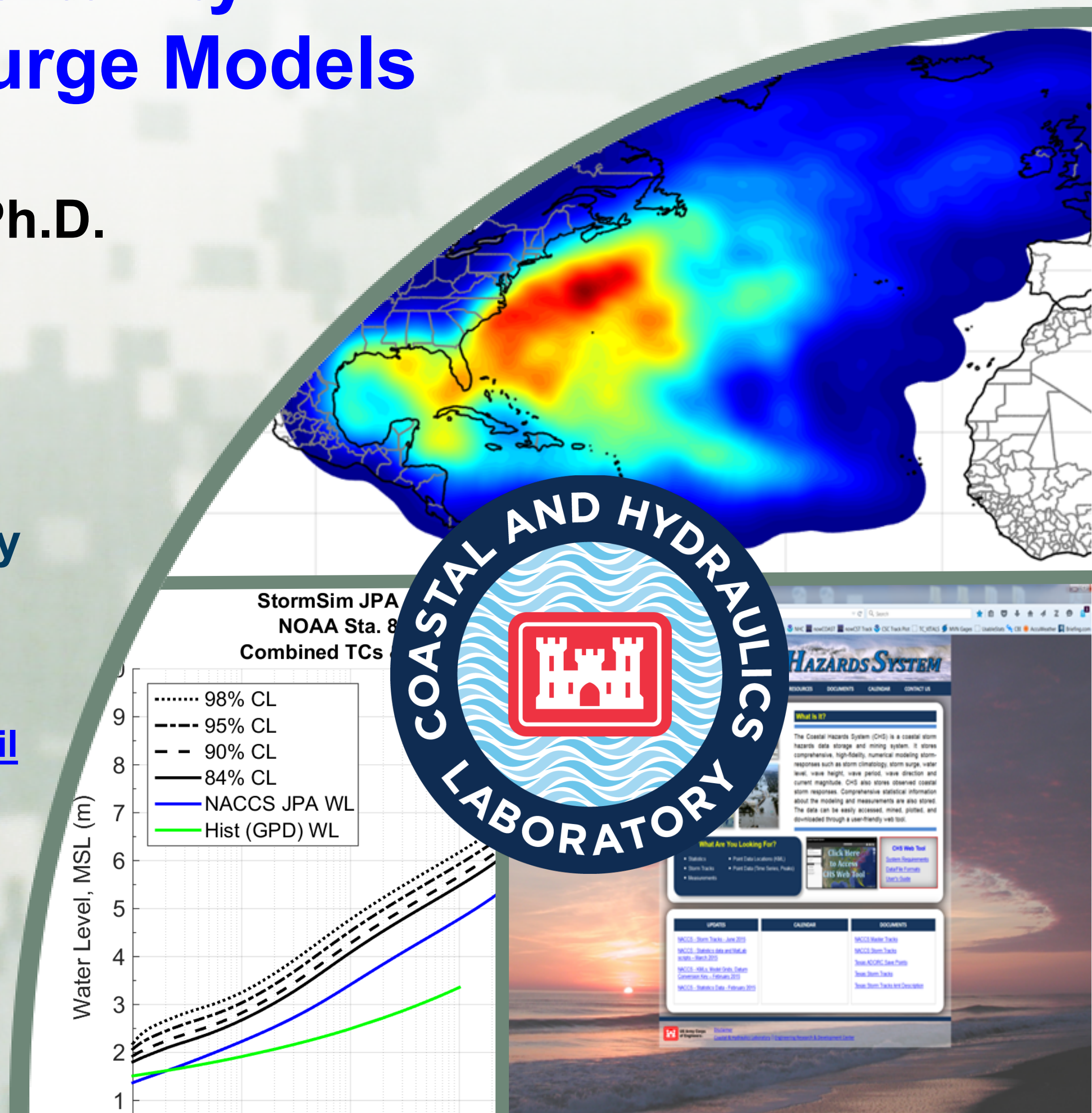
Quantification of Uncertainty in Probabilistic Storm Surge Models

Norberto C. Nadal-Caraballo, Ph.D.

Team: Victor Gonzalez, P.E.
Amanda B. Lewis
Efrain Ramos-Santiago

Coastal and Hydraulics Laboratory
US Army Engineer R&D Center

Norberto.C.Nadal-Caraballo@usace.army.mil



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Outline

- Introduction
  - Objectives and treatment of uncertainty
  - Project tasks
  - Logic tree approach
- Storm Recurrence Rate models
- Marginal (univariate) Distributions
- Generating Synthetic Storm Sets
- Characterization & Propagation of Uncertainty

Introduction

- Study objectives:
  - Identification of technically defensible data sources, models, and methods for the computation of storm surge.
  - Assessment for carrying forward for evaluation of epistemic uncertainty.
- Treatment of uncertainty in present study:
  - Follows probabilistic seismic hazard analysis (PSHA).
  - Epistemic uncertainty is quantified and propagated through logic tree approach.
  - Differences between a numerical model and the natural phenomenon is prevalent (error term) → **aleatory**
  - Reduction of uncertainty in the selection and application of alternative data, methods, and models → **epistemic**

Project Overview (Tasks)

- Task 1 Literature Review
- Task 2 Storm Recurrence Rate Models
- Task 3 Defining Joint Probability of Storm Parameters
- Task 4 Generating Synthetic Storm Simulation Sets
- Task 5 Probabilistic Modeling of Numerical Surge Simulation Errors
- Task 6 Synthesis and Final Report Preparation
- Task 7 Transfer of Knowledge

Logic Tree Approach

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:

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

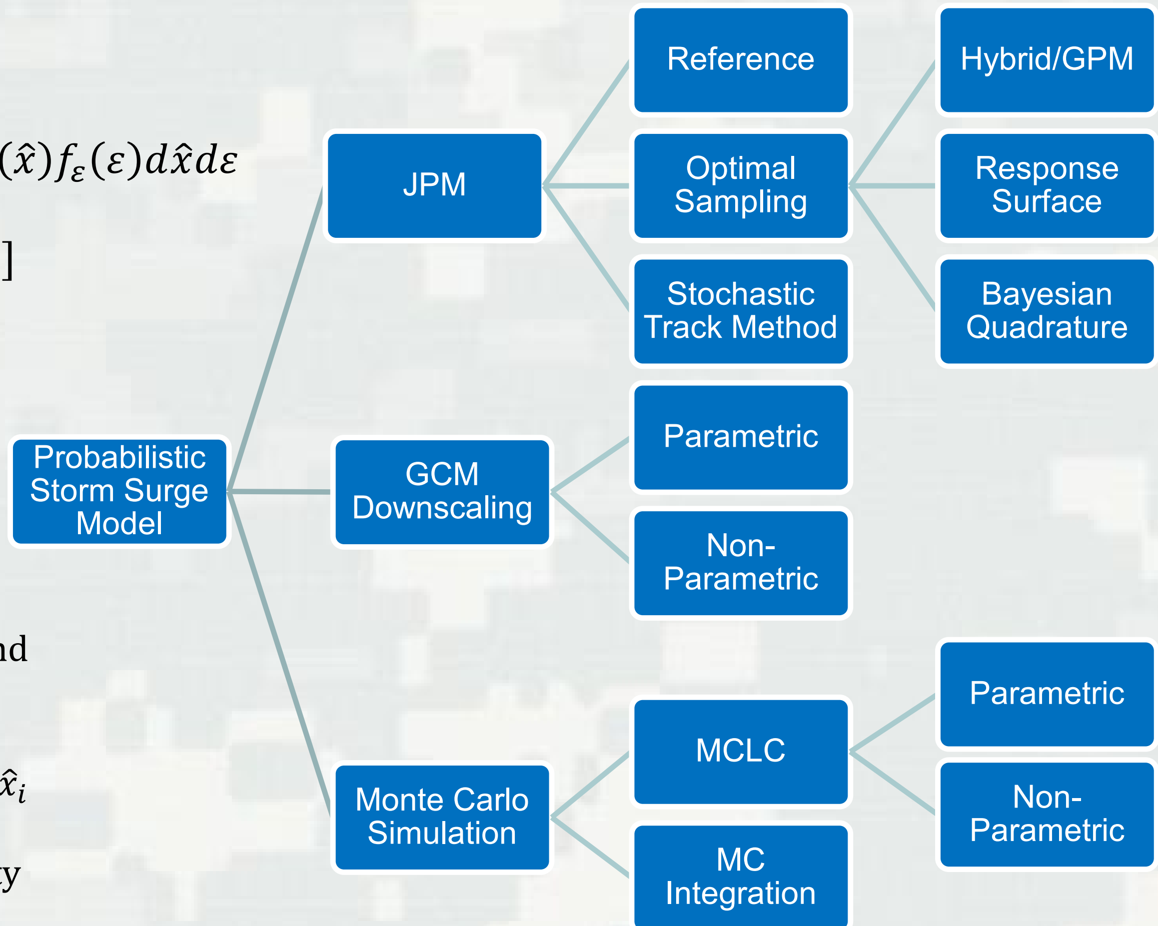
$\hat{x} = f(x_o, \theta, \Delta p, R_{max}, V_t)$

λ = SRR (storms/yr/km)

$\hat{\lambda}_i$ = probability mass (storms/yr) or $\lambda\, p_i$, with p_i=product of discrete probability and TC track spacing (km)

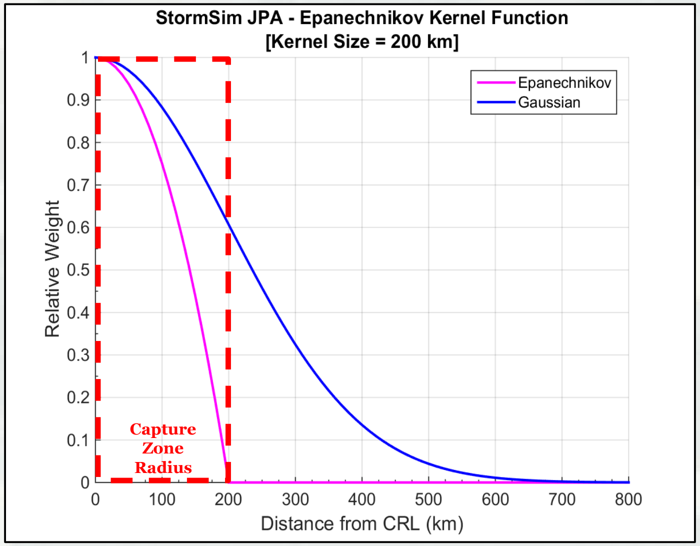
$P[r(\hat{x}) + \varepsilon > r|\hat{x}, \varepsilon]$ conditional probability that storm i with parameters $\hat{x}_i$ generates a response larger than r

ε = unbiased error or aleatory uncertainty of r



Task 2: Epistemic Uncertainty in SRR Models

- Data sources and methods used for the computation of site-specific storm recurrence rate (SRR) models.
- Models for Calculating SRR
  - Uniform kernel function (UKF) or capture zone
  - Gaussian kernel function (GKF)
  - Epanechnikov kernel function (EKF)
- Topics
  - Investigate SRR aleatory uncertainty.
  - Compare Models for Estimation of SRR & Impact on Hazard Curves.



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

$$w(d_i) = \frac{1}{h_d}\begin{cases} 0.5, & if \left|\frac{d_i}{h_d}\right| < 1 \\ 0, & otherwise \end{cases}$$

UKF

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

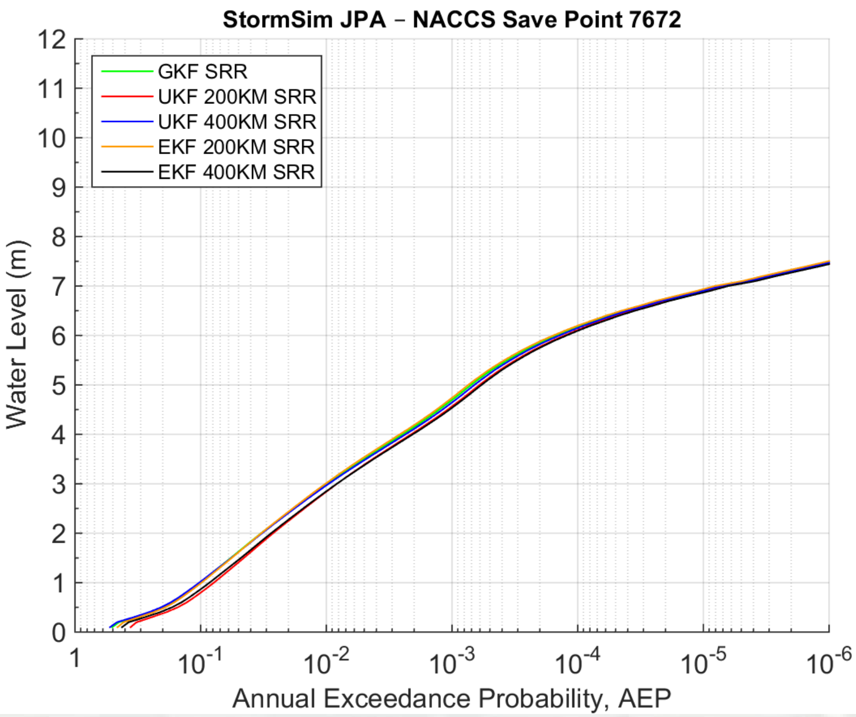
GKF

$$w(d_i) = \frac{1}{h_d}\begin{cases} \frac{3}{4}\left[1 - \left(\frac{d_i}{h_d}\right)^2\right], & if \left|\frac{d_i}{h_d}\right| < 1 \\ 0, & otherwise \end{cases}$$

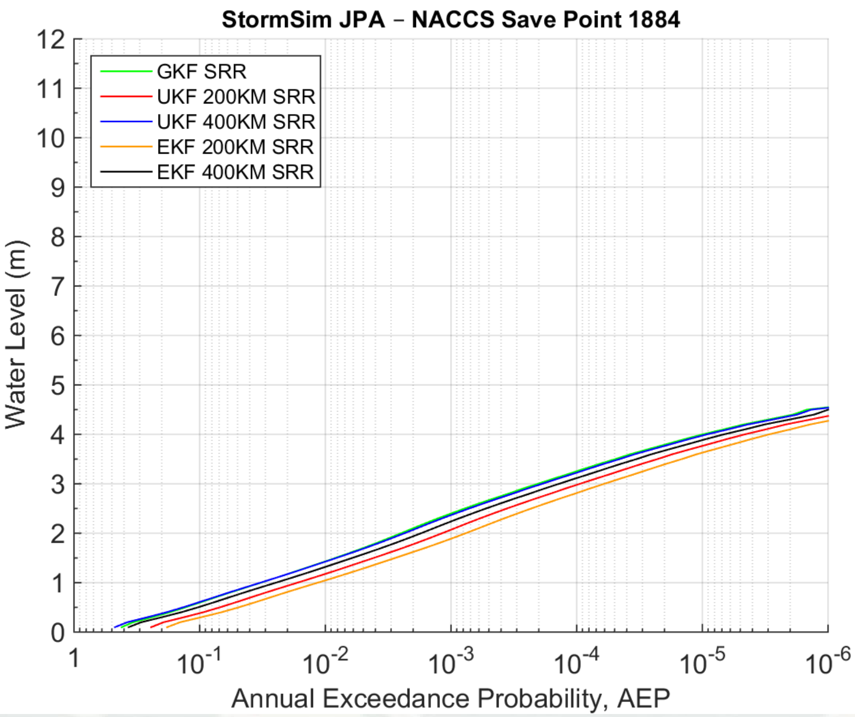
EKF

Task 2: Epistemic Uncertainty in SRR Models

- Effect of Kernel functions and sizes on WL hazard curve



The Battery, NY



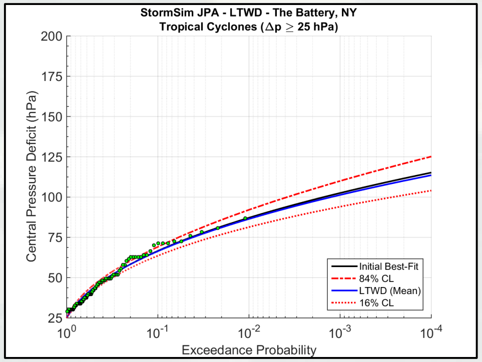
Boston, MA

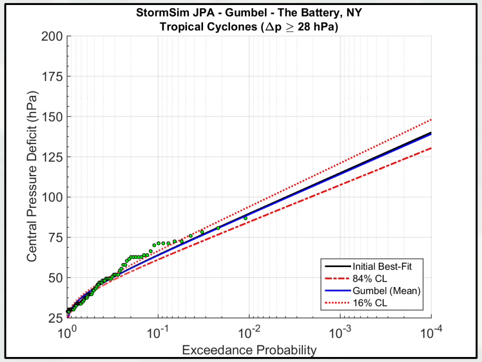
Task 2: Epistemic Uncertainty in SRR Models

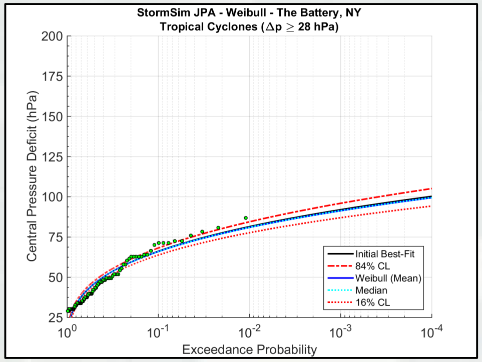
- **Findings**
  - The lower SRR uncertainty was associated with locations with higher TC occurrences (sample size).
  - Kernel function introduces small variability in hazard curve.
  - Relative contributions of aleatory uncertainty ($\Delta p \geq 28$ hPa)
    - Sampling uncertainty – 65%
    - Selected period of record – 19%
    - Gaussian kernel size – 15%
    - Observational data – 1%
  - Although resampling uncertainty and observational uncertainty could be classified as aleatory variability, they could also be considered epistemic from the point of view of reducibility.
    - Passage of time → increase sample size
    - Improvement in observation technologies → increase measurement accuracy
    - Discretized and incorporated as branch in logic tree.

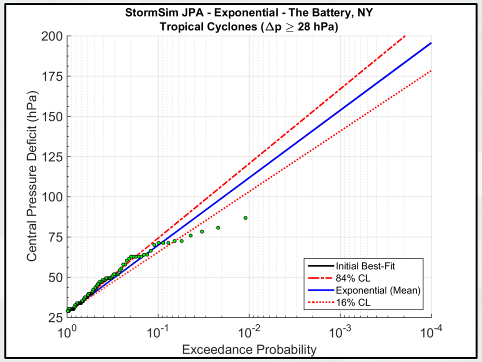
Task 3: Data, Models and Methods for Defining Joint Probability of Storm Parameters

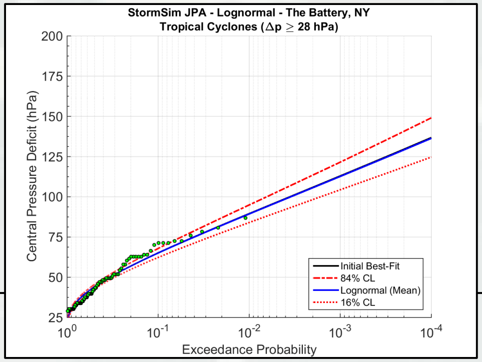
- **Task Description**
  - Identification of technically defensible TC parameter data sources, screening methods, and parameterization schemes for development of probability distribution.
- **Topics:**
  - Selection of probability distributions
  - Evaluate technically defensible data sources







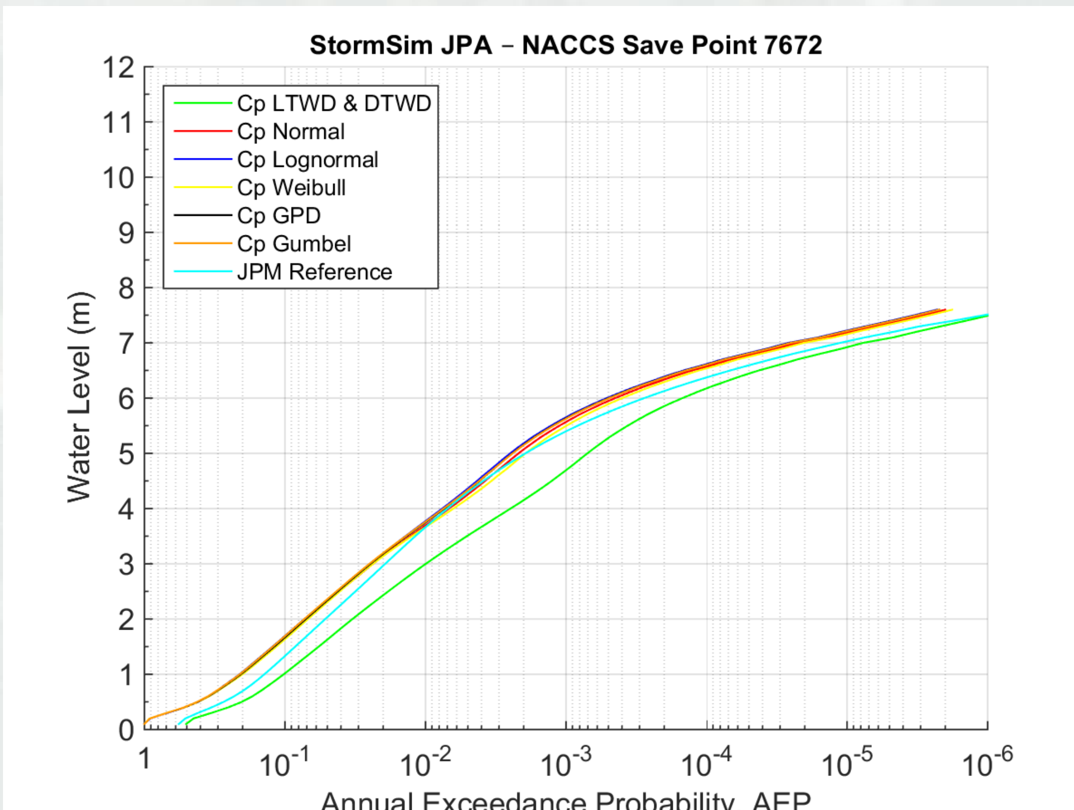




Δp Examples

Task 3: Data, Models and Methods for Defining Joint Probability of Storm Parameters

- Effect of selection of Δp distribution on hazard curve



LTWD & DTWD curve considers the discretization of TCs into high and low intensity.

The effect is to lower the hazard curve.

Choice of Δp distribution showed limited impact

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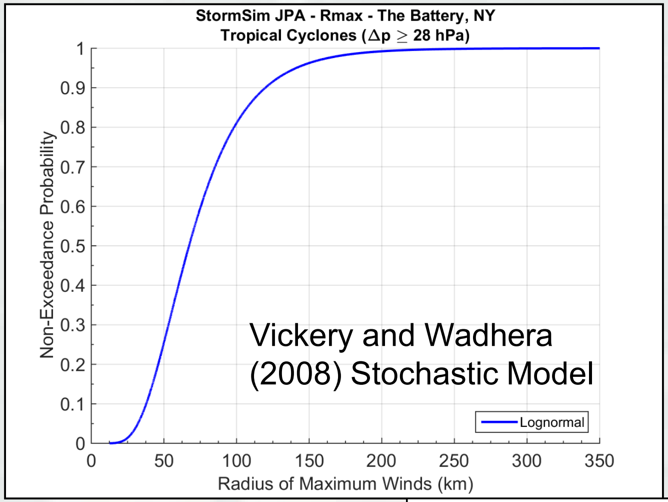
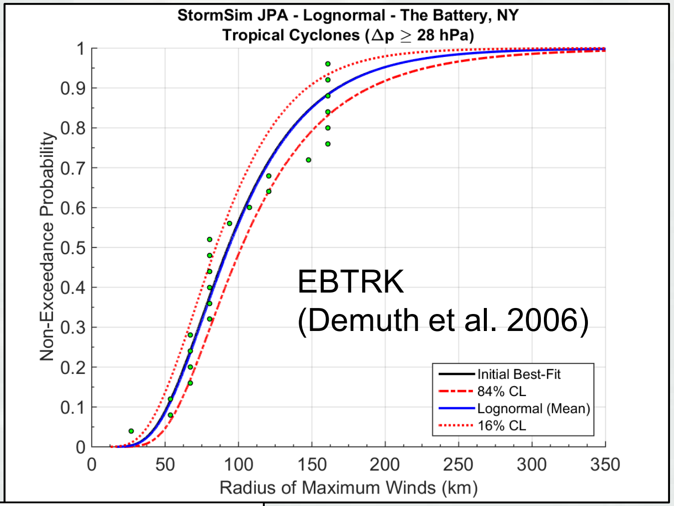
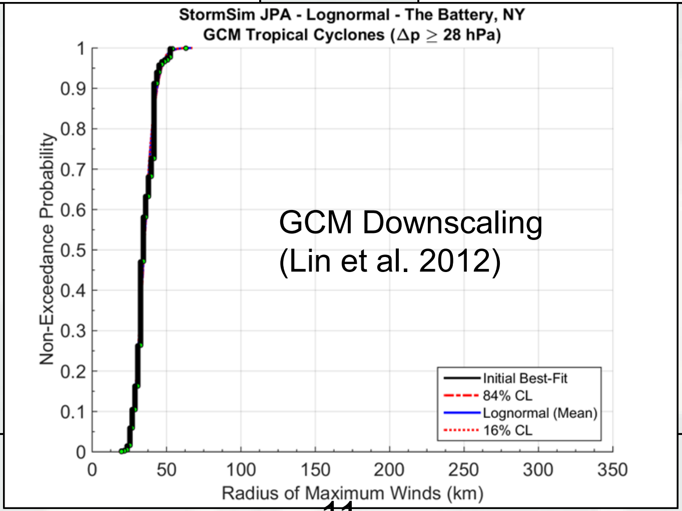
Task 3: Data, Models and Methods for Defining Joint Probability of Storm Parameters

- Comparison of R_{max} probability distributions





Similar curves resulting from the Vickery model and EBTRK reanalysis.



GCM plot suggests that extratropical transition of TCs is not being adequately represented.

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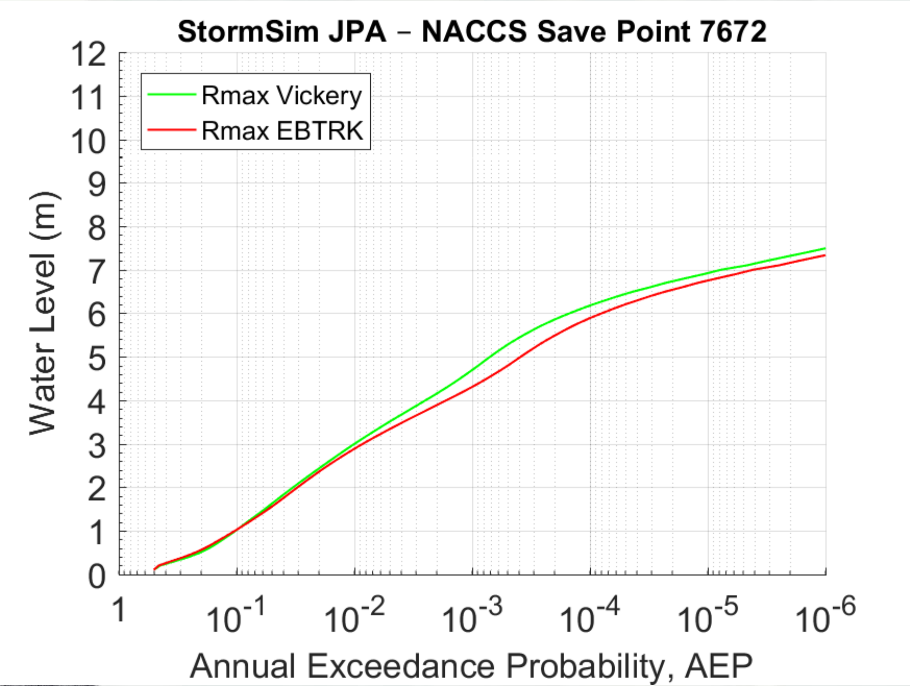
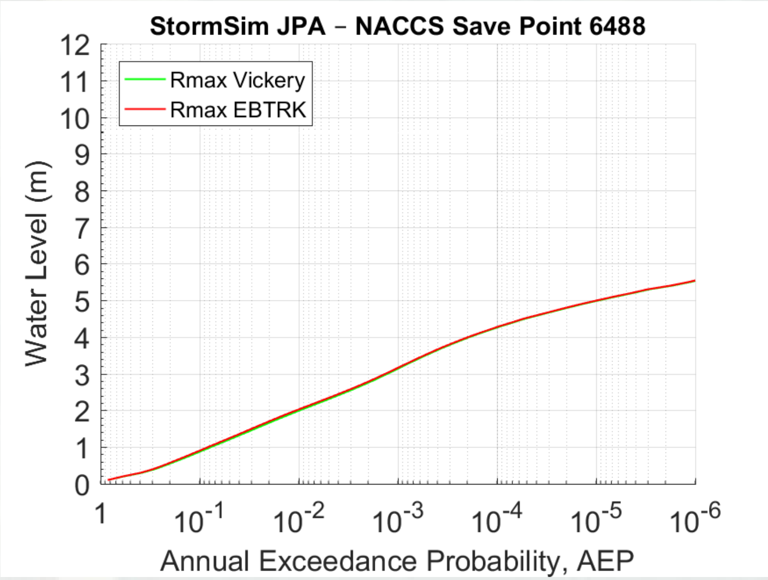
Task 3: Data, Models and Methods for Defining Joint Probability of Storm Parameters

- Vickery and Wadhera and EBTRK R_{max} hazard curves



The Battery, NY



Virginia Beach, VA

Small variation in hazard curves for EBTRK and Vickery and Wadhera (2008) stochastic model → **both lognormal.**

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Task 3: Data, Models and Methods for Defining Joint Probability of Storm Parameters

- **General Findings**
  - The most relevant factor in choosing distribution type was how well it described the low-frequency tails.
  - More than one statistical distribution could be valid for a given TC parameter.
  - Comparison of viable fits usually did not reveal significant differences. Limited effect confirmed by hazard curve comparisons.
  - The sampling technique used for the generation of synthetic TCs may lessen the significance of selecting a given probability distribution for large discretization intervals.
  - The judgment of carry forward a given dataset, method, or model was found to be highly dependent on the location.

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- Task Description
  - Capture full range of technically defensible data and methods for generating synthetic storm sets required to fully characterize and propagate uncertainties in storm surge estimates.
  - Methods tested for generating synthetic storm simulation sets
    - JPM Reference – 74,430 TCs
    - JPM-OS – 1,050 TCs
    - Monte Carlo Simulation: Life Cycle – 211,997 TCs & Integration – 211,997 TCs
    - CGM Downscaling – 1,470 TCs
    - Methods for calculating probability mass that explicitly consider parameter correlations – 211,997 TCs
      - Multivariate Gaussian Distribution
      - Multivariate Gaussian Copula
      - Multivariate Student's t Copula

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- **Reference Set**
  - Traditional JPM approach → All parameter combinations →Large set of storms (74,430 TCs)
  - A Gaussian process metamodel (GPM) (Jia et al. 2016) was used to develop tens of hundreds of TCs.
    - The GPM is conceptually similar to response surface.
      - initial discretization of the joint probability distribution is refined by regression or interpolation of storm surge from additional TC parameter combinations.
    - The GPM used in this study was trained using the 1050 synthetic TCs developed as part of the NACCS (Nadal-Caraballo et al. 2015).

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

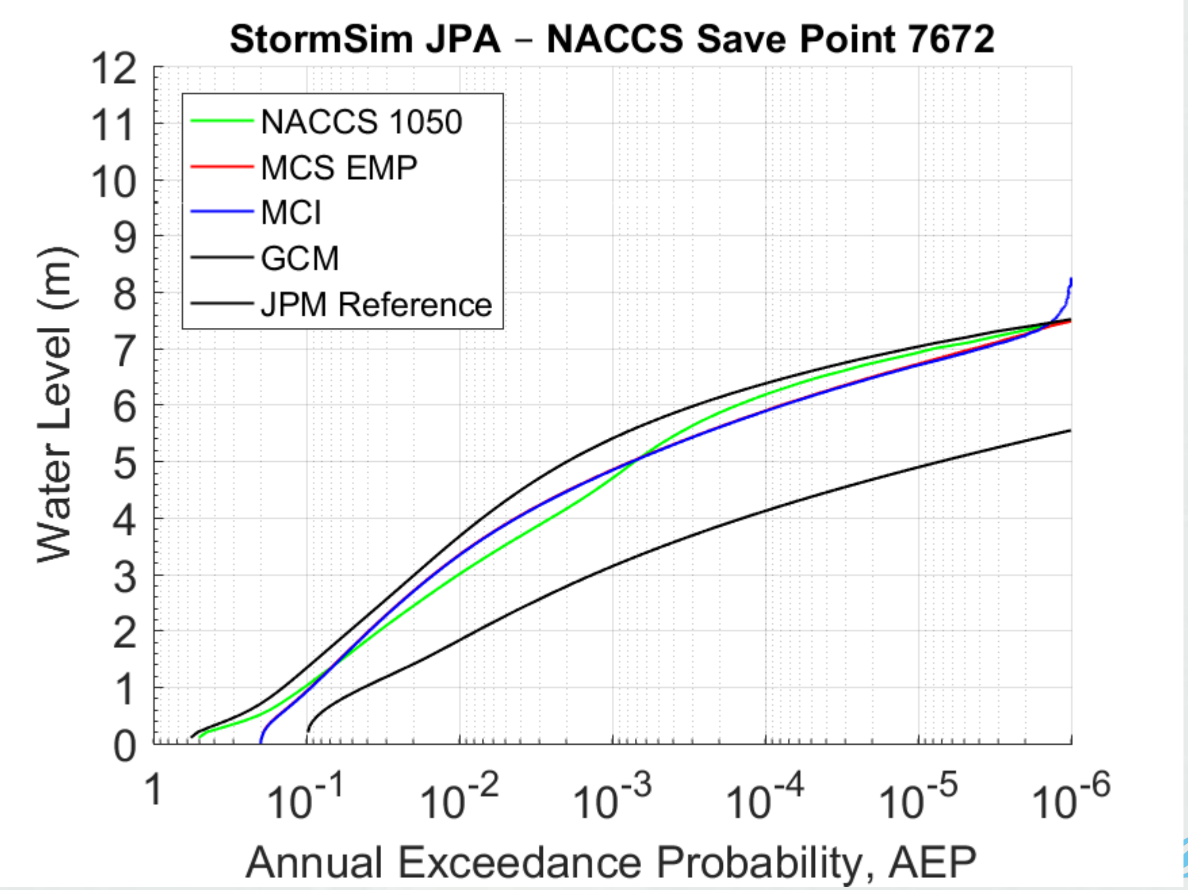
- **Monte Carlo Simulation**
  - **Monte Carlo Life-Cycle**
    - Univariate distributions of TC parameters were sampled for a 1,000,000-yr period, which resulted in 200,000+ TCs.
    - **No probability masses** required.
      - TC's sampled based on their likelihood of occurrence and joint p. Storm surge hazard curve from **empirical distribution** (Weibull plotting position).
    - Mean hazard curve and confidence levels calculated through bootstrap resampling using replicated storm surge values with added discretized uncertainty.
- **Monte Carlo Integration (MCI)** (Wyncoll and Gouldby 2015)
    - Probabilities are calculated as the percent of TCs with response greater than a set of surge elevation bins. **No probability masses** required.
    - $P(C > c) \approx \frac{L_c}{L} * \lambda$, where L_c is the number of Monte Carlo realizations that exceed c, L is the total number of Mote Carlo realizations, and λ is the sample intensity (storms/yr).

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- **GCM Downscaling** (Lin et. al 2012)
  - Storm surges determined by GCM-driven statistical/deterministic hurricane model with hydrodynamic surge models.
  - Synthetic TCs tracks are generated according to large-scale atmospheric and ocean environments rather than historical TCs.
  - 1,470 tracks covering a time period from 1970-2010.
  - The storm surge responses were simulated by applying GCM parameters and tracks to the previously trained GPM
  - Stochastic simulation technique (SST) consisting of combined empirical and GPD fits was applied to the storm surge values to obtain hazard curve.

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- **Methods hazard curves comparison**

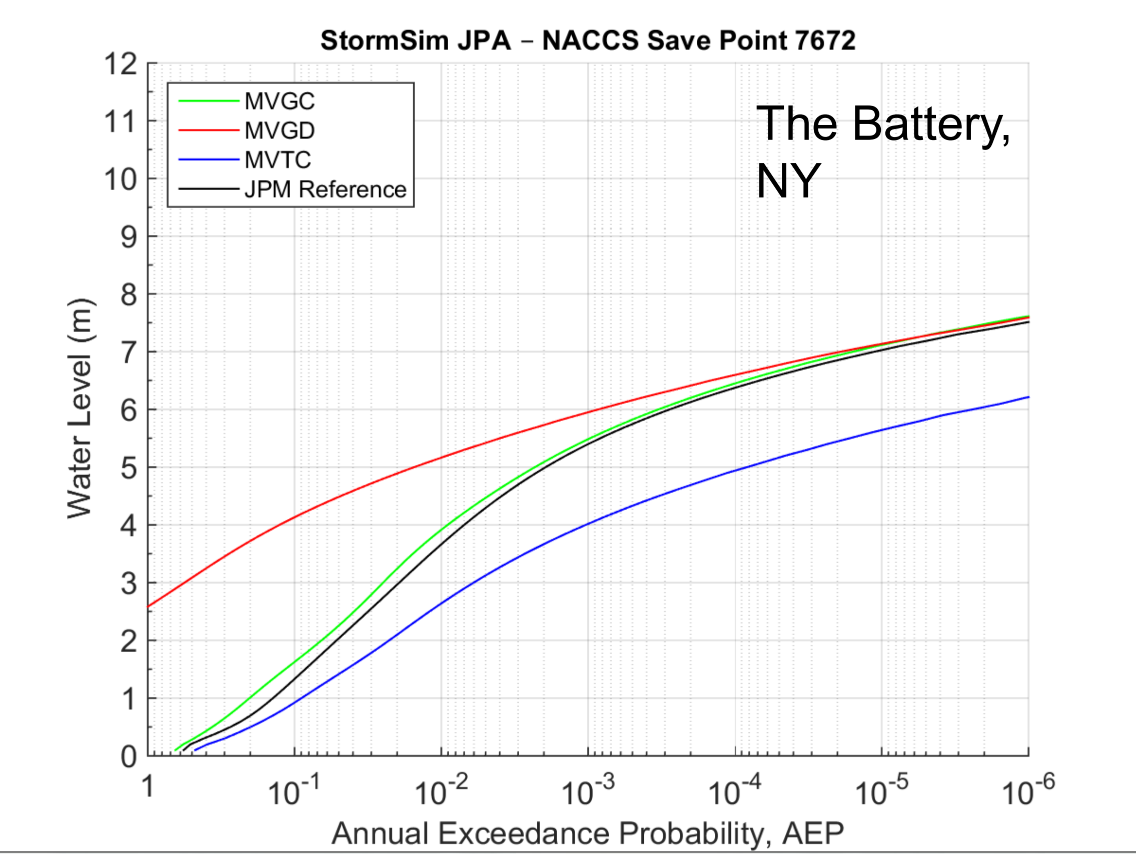


Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- Additional methods for calculating probability masses.
  - Multivariate Gaussian Distribution (MVGD)
  - Multivariate Gaussian Copula (MVGC)
  - Multivariate Student's t Copula (MVTC)
- Characteristics:
  - Methods maintain parameter dependencies.
  - Marginal distributions are defined for each parameter
  - The only one where the correlation between Dp and Rm be modified is Gaussian Copula.

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

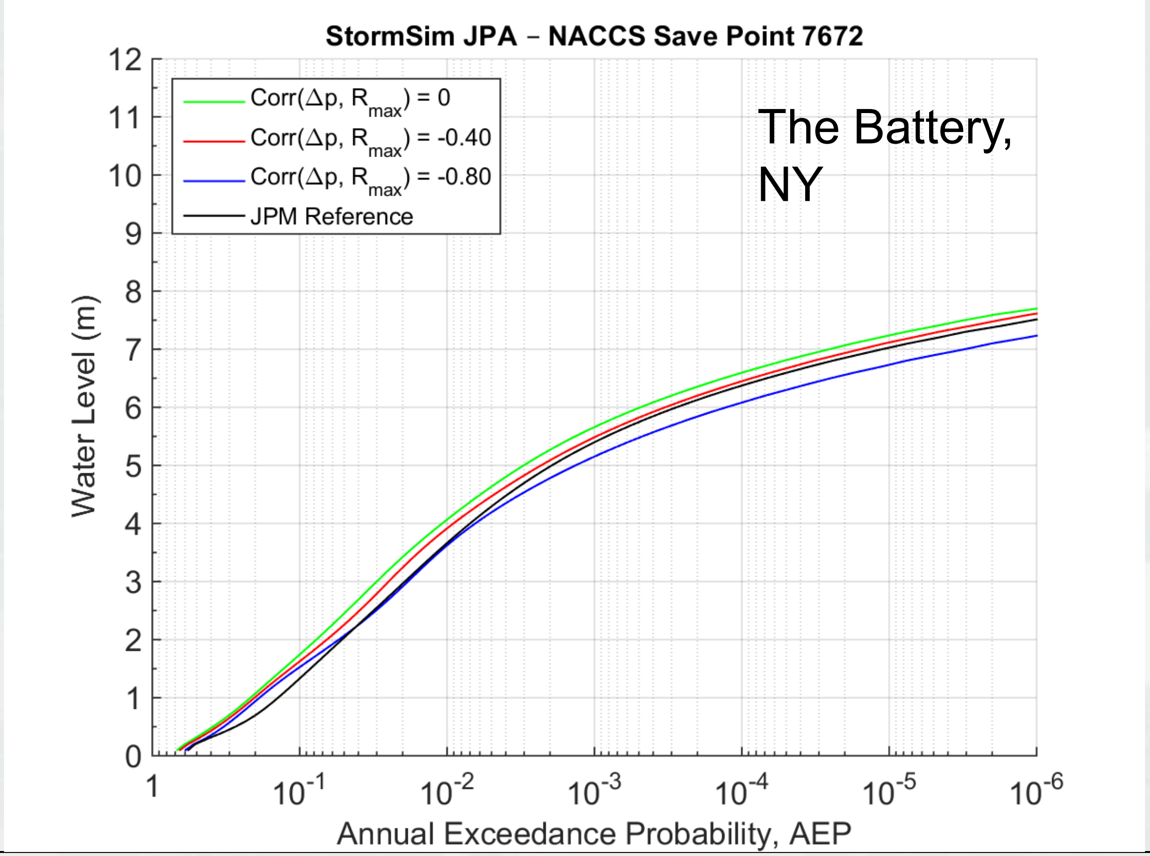
- MVGD, MVGC, and MVTC comparison



MVGC shows more agreement with the JPM Reference hazard curve

Task 4: Data, Models, and Methods for Generating Synthetic Storm Simulation Sets

- MVGC: correlation between Δp and R_{max}



The two are negatively correlated

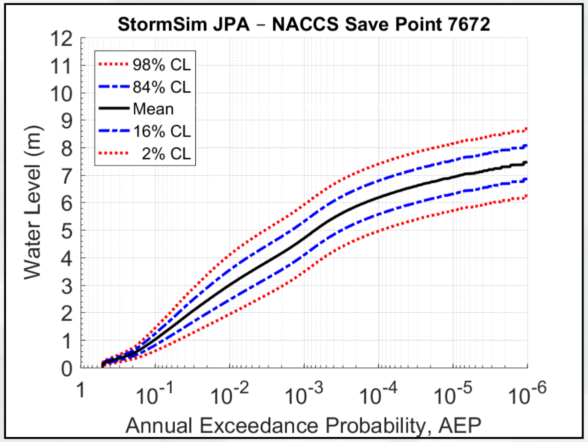
Independence between the two parameters results in more combinations of high intensity and large radius → larger surge

Task 5: Approaches for Probabilistic Modeling of Numerical Surge Simulation Errors

- **Task Description**
  - Investigate approaches for characterizing and modeling errors within the probabilistic framework constituted by modeling of storm surge.
  - Topics:
    - Comparison of approaches for the characterization of uncertainty
      - Constant uncertainty (e.g. 0.61m)
      - Proportional uncertainty (e.g. 20%)
      - Combined constant and proportional uncertainty [e.g., min(20%, 0.61m)]
    - The significance of different number of discrete values (or random samples) from the Gaussian distribution will be evaluated by comparing results using 30, 100, 300,1000, and 3000 values.

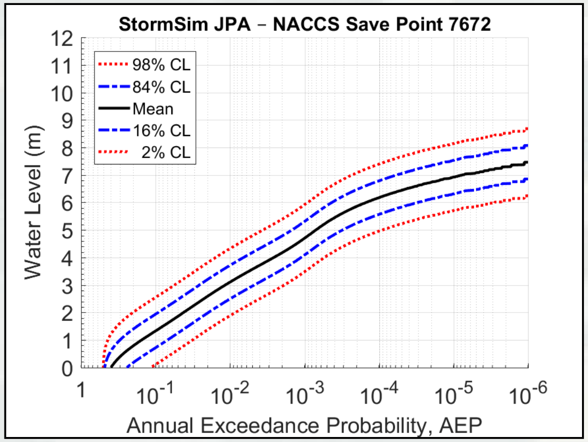
Task 5: Approaches for Probabilistic Modeling of Numerical Surge Simulation Errors

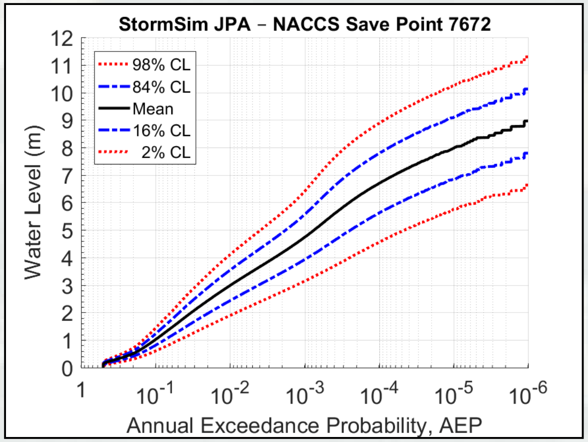
- **Results – Characterization of Uncertainty**



Uncertainty = min(20%, 0.61m)

Constant Uncertainty = 0.61 m

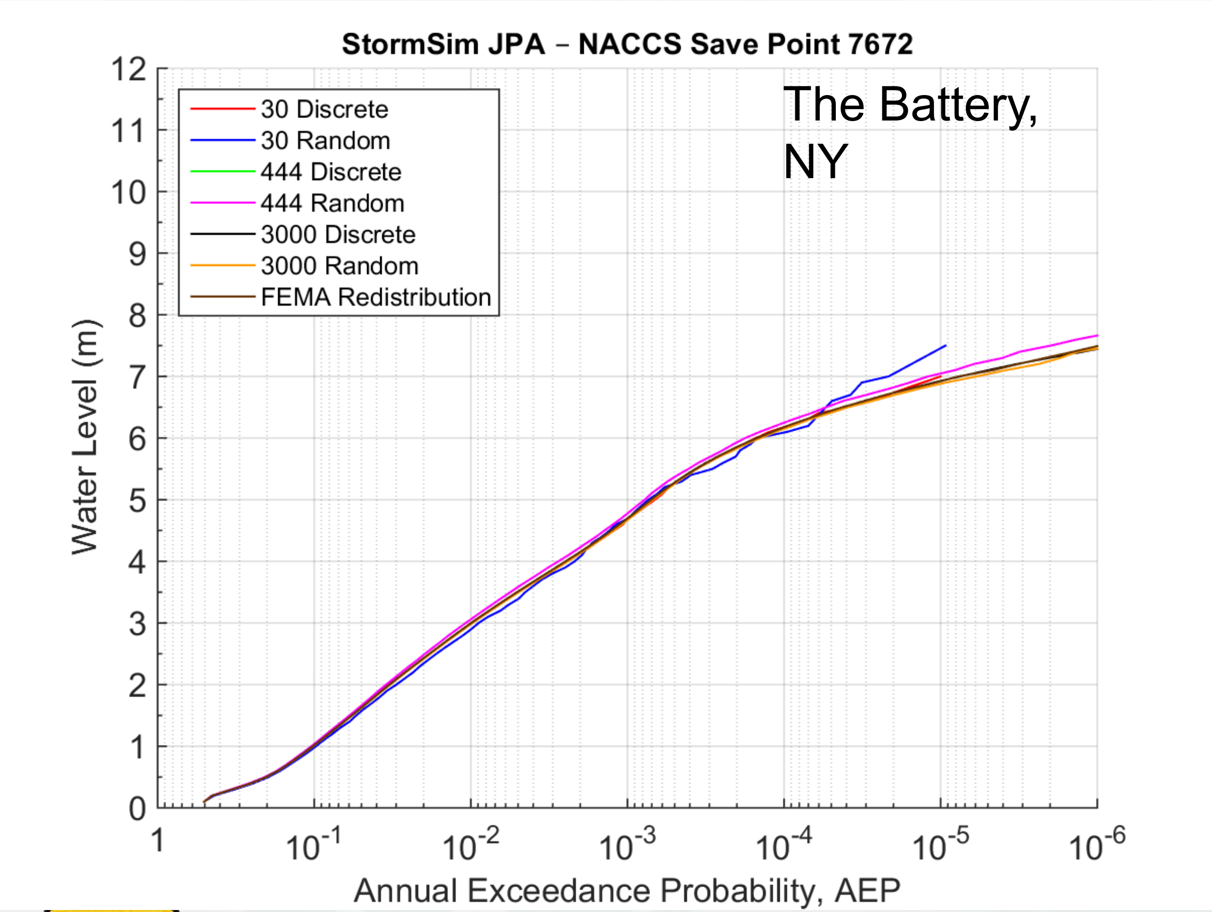




Proportional Uncertainty = 20%

Task 5: Approaches for Probabilistic Modeling of Numerical Surge Simulation Errors

- Incorporating uncertainty in the integration



$WL \rightarrow WL_1, WL_2 \ldots WL_n$

$n =$ number of times WL is replicated and normal distribution discretized or number of times it is sampled.

$$WL_n = \mu + \sigma(Z^*)$$

Z^*=

Discrete (Z_1 … Z_n)

Randomly sampled (Z_1 … Z_n)

Random sampling increases hazard curve tail for 30 and 444 partitions.

FEMA redistribution and 444 partitions were equivalent

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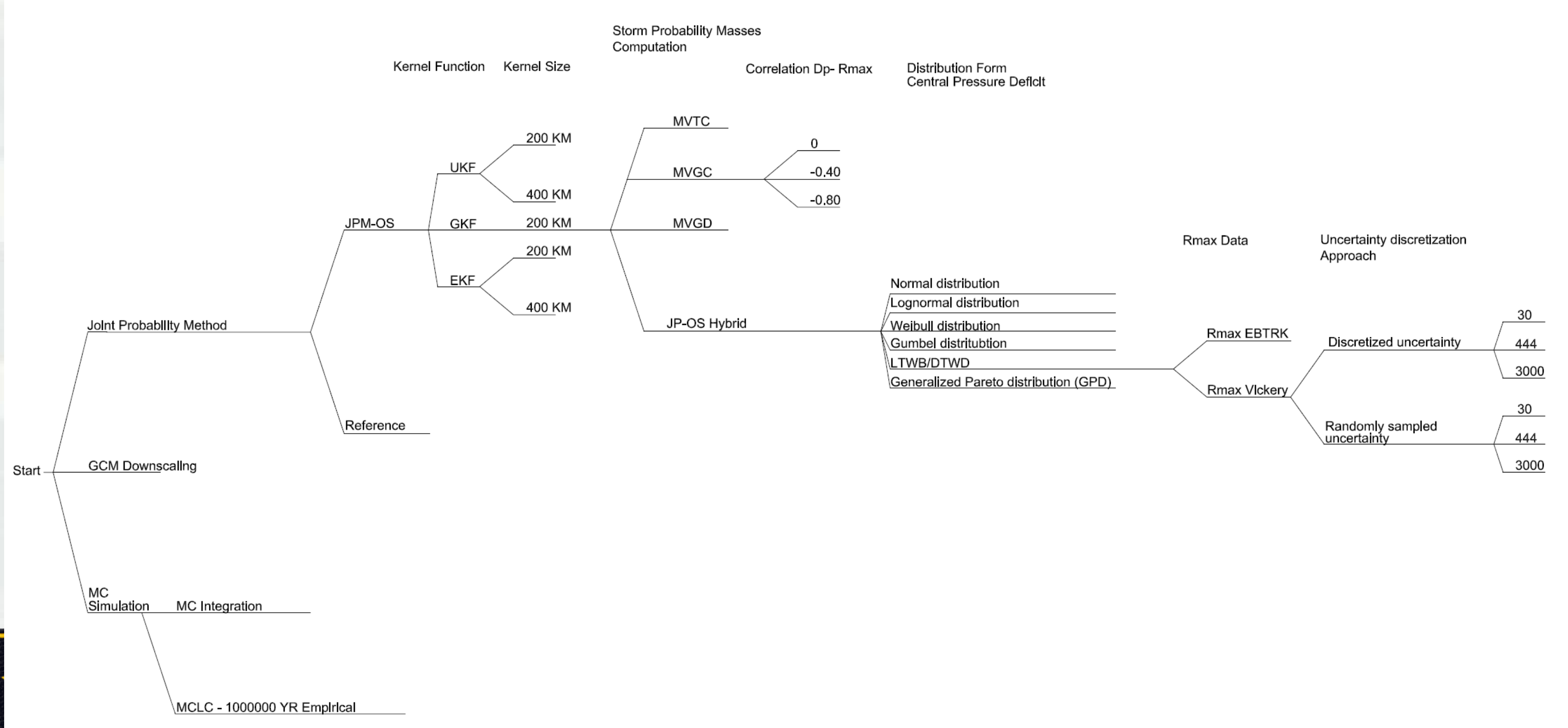
Task 6: Synthesis

- **Task Description**
  - ► Develop approach to characterize, quantify, and propagate both aleatory and epistemic uncertainties through the probabilistic framework of storm surge assessment process in order to develop robust flood hazard curves for use in NPPs applications.
  - ► Topics:
    - Treatment of uncertainty (Logic trees)

Task 6: Synthesis

- Preliminary example: Surge hazard logic tree



Task 6: Synthesis

- Logic tree table and weight assignment

Number	Description	Step 1	Step 2 JPM method	Step 3 kernel function	Step 4 kenrel size	Step 5 ProbMass	Step 6 Corr	Step 7 Distribution	Step 8 Rmax	Step 9 Discretization	Step 10 # Discretizations	Weight
1	JPM-OS UKF 200km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 444			0.1	0.75	-	-	-	-	-	-	0.042
2	JPM-OS UKF 400km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 444				0.25	-	-	-	-	-	-	0.014
3	JPM-OS EKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 444			0.1	0.75	-	-	-	-	-	-	0.042
4	JPM-OS EKF 400 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 444				0.25	-	-	-	-	-	-	0.014
5	JPM-OS GKF 200 km MVTC				-	0.025	-	-	-	-	-	0.011
6	JPM-OS GKF 200 km MVGD				-	0.025	-	-	-	-	-	0.011
7	JPM-OS GKF 200 km MVGC zero corr				-		0.1	-	-	-	-	0.009
8	JPM-OS GKF 200 km MVGC -0.4 corr				-	0.2	0.8	-	-	-	-	0.072
9	JPM-OS GKF 200 km MVGC -0.80 corr				-		0.1	-	-	-	-	0.009
10	JPM-OS GKF 200 km JPM-OS Hybrid Lognormal Cp Rmax Vickery Discretized 444		0.75		-		-	0.1	-	-	-	0.034
11	JPM-OS GKF 200 km JPM-OS Hybrid Weibull Cp Rmax Vickery Discretized 444	0.75			-		-	0.1	-	-	-	0.034
12	JPM-OS GKF 200 km JPM-OS Hybrid Gumbel Cp Rmax Vickery Discretized 444			0.8	-		-	0.15	-	-	-	0.051
13	JPM-OS GKF 200 km JPM-OS Hybrid GPD Cp Rmax Vickery Discretized 444				-		-	0.15	-	-	-	0.051
14	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax EBTRK				-		-		0.25	-	-	0.042
15	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 30				-	0.75	-				0.05	0.005
16	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 444				-		-			0.8	0.7	0.071
17	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Discretized 3000				-		-	0.5	0.75		0.25	0.025
18	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Random 30				-		-				0.05	0.001
19	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Random 444				-		-			0.2	0.7	0.018
20	JPM-OS GKF 200 km JPM-OS Hybrid LTWD/DTWD Rmax Vickery Random 3000				-		-				0.25	0.006
21	JPM Reference		0.25	-	-	-	-	-	-	-	-	0.188
22	GCM	0.05	-	-	-	-	-	-	-	-	-	0.050
23	MCLC	0.2	-	-	-	-	-	-	-	-	-	0.200
	SUM											1.000

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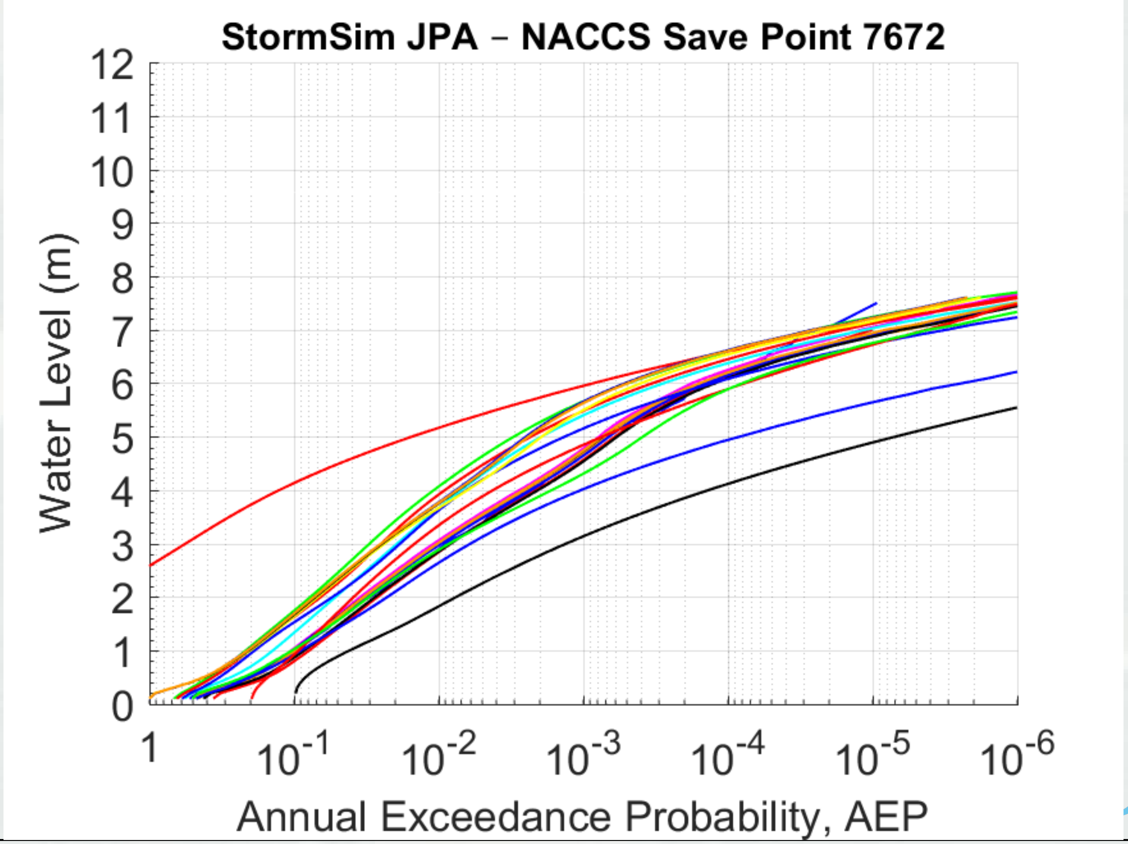
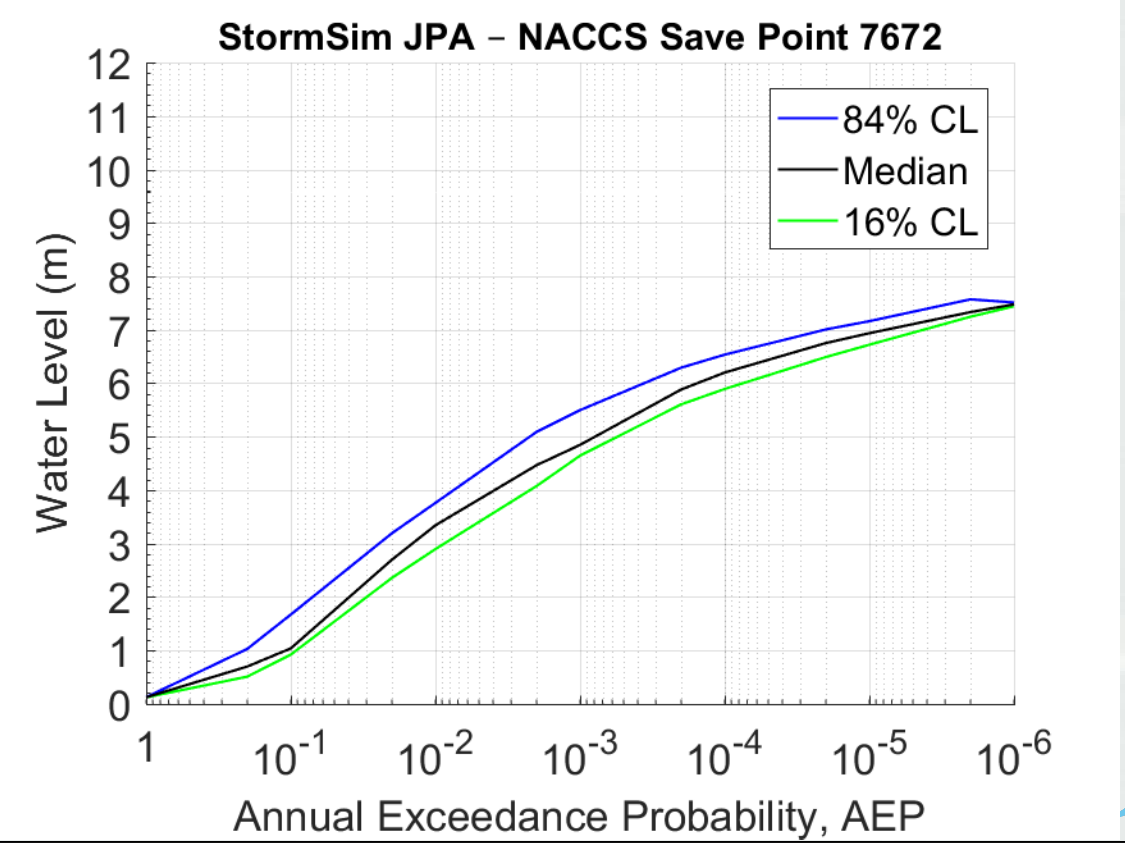
Task 6: Synthesis

- Family of hazard curves



Task 6: Synthesis

- Median hazard curve with confidence limits



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References

- Chouinard, L., C. Liu, and C. Cooper. 1997. Model for Severity of Hurricanes in Gulf of Mexico. *Journal of Waterway, Port, Coastal, and Ocean Engineering* 123 (3): 120–129.
- Demuth, J., M. DeMaria, and J.A. Knaff, 2006: Improvement of advanced microwave sounder unit tropical cyclone intensity and size estimation algorithms. *Journal of Applied Meteorology and Climatology*, 45: 1573-1581.
- Jia, Gaofeng, A. A. Taflanidis, N. C. Nadal-Caraballo, J. A. Melby, A. B. Kennedy, and J. M. Smith. 2016. Surrogate Modeling for Peak or Time-Dependent Storm Surge Prediction over an Extended Coastal Region Using an Existing Database of Synthetic Storms. *Natural Hazards* 81 (2): 909–938.
- Lin, Ning, K Emanuel, M. Oppenheimer, and E. Vanmarcke. 2012. Physically Based Assessment of Hurricane Surge Threat under Climate Change. *Nature Climate Change* 2 (6): 462–467.
- Nadal-Caraballo, N.C., J.A. Melby, V.M. Gonzalez, and A.T. Cox. 2015. North Atlantic Coast Comprehensive Study – Coastal Storm Hazards from Virginia to Maine. ERDC/CHL TR-15-5. 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.
- Wyncoll, D., and B. Gouldby. 2015. Integrating a Multivariate Extreme Value Method within a System Flood Risk Analysis Model. *Journal of Flood Risk Management* 8 (2): 145–160.

Contact Information

U.S. Army Engineer R&D Center

Coastal and Hydraulics Laboratory

Norberto C. Nadal-Caraballo, Ph.D.

Phone: (601) 634-2008

Email: Norberto.C.Nadal-Caraballo@usace.army.mil

U.S. Nuclear Regulatory Commission

Joseph F. Kanney, Ph.D.

Phone: (301) 980-8039

Email: Joseph.Kanney@nrc.gov