SURROGATE MODELING OF STORM RESPONSE

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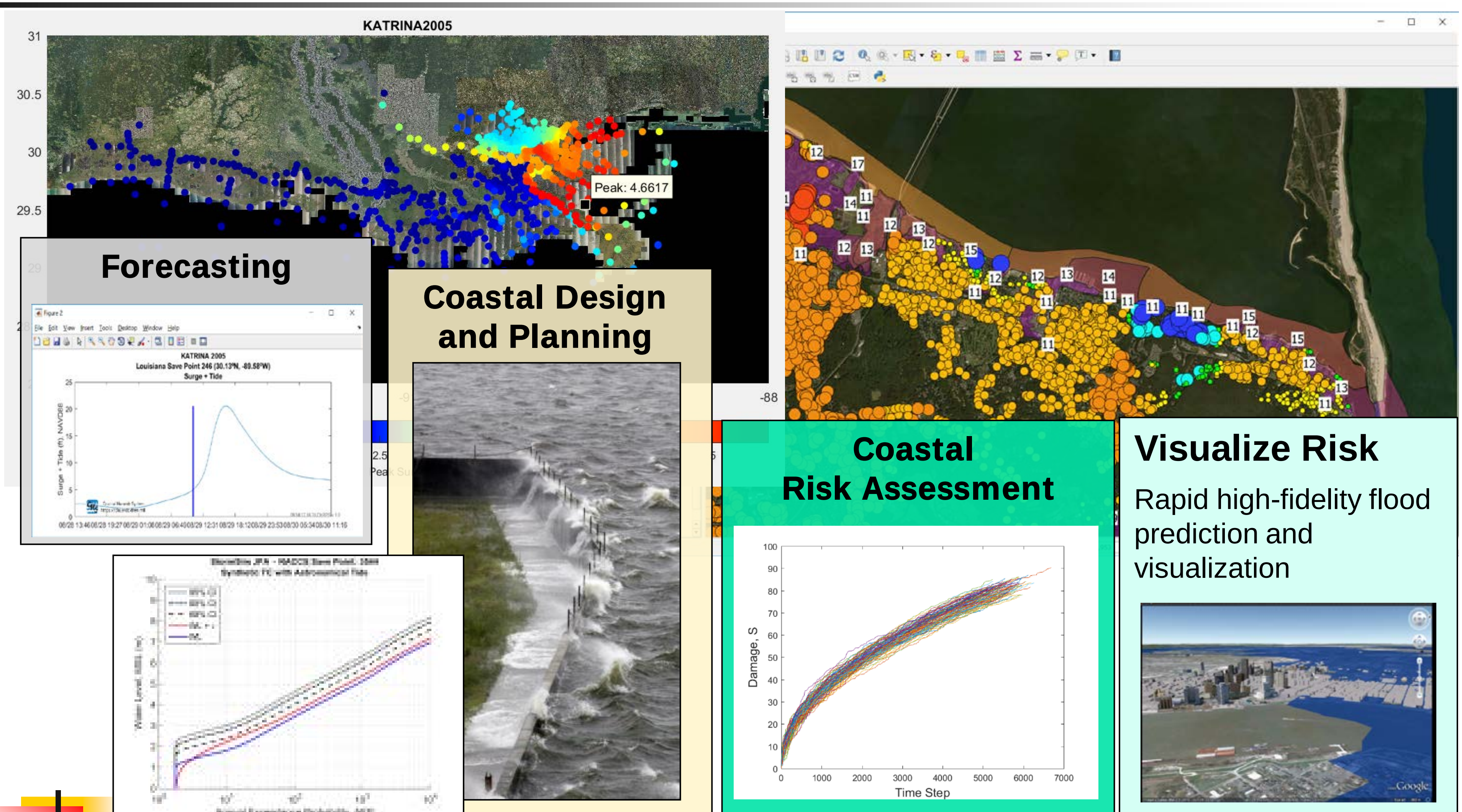
Probabilistic Coastal Hazard Assessment



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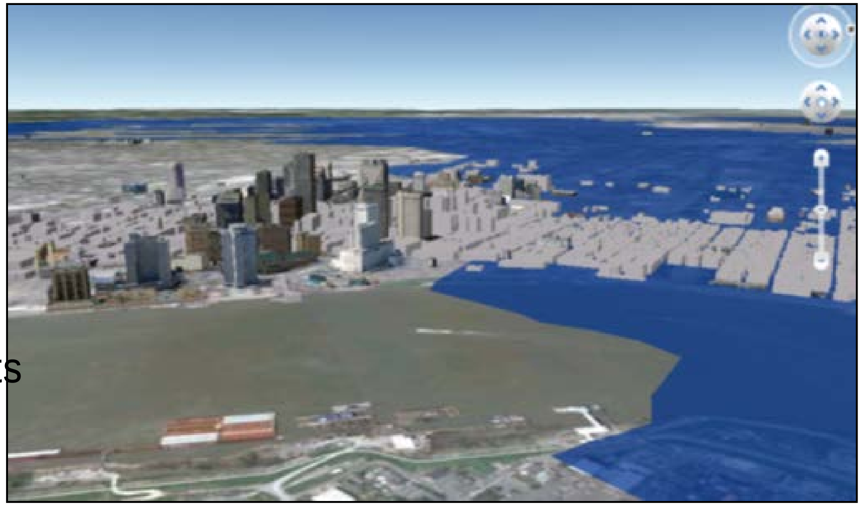
Presentation for ICCE 2018

Specific Objectives

- **High-fidelity Surrogate Models** for Hurricane Response
  - Rapid prediction of response: inundation (surge+tide), wave height, wave period, wave direction, currents, wind speed, wind direction
  - For hurricane water levels, use coastal hazards system and NOAA forecast inputs
  - **For wave transmission, use CHS, buoy data, or WIS as inputs**
  - Robust surrogate parameterization
  - Uncertainty



- **Centralized computation/distribution - Coastal Hazards System**
- **Stand-alone PC software - StormSim**

Surrogate Modeling

Surrogate Techniques: Data Driven

- Least squares regression
- Low dimensional spline interpolation
- Dimensional functions
- Polynomial chaos
- Response surface approximations
- **Artificial neural networks**
- **Kriging or Gaussian process emulation**

Kriging Implementation

n_x: input dimension (hurricane characteristics)
n_z: output dimension (surge response at different locations)
n: number of experiments (storms in database)

$R(\mathrm{x}^l,\mathrm{x}^m|\mathrm{s})$: correlation function with hyper-parameters s (tuning)
$f(\mathrm{x})$: basis (trend) functions

Experiment matrix: $\mathbf{X} = [\mathbf{x}^1 \; \ldots \; \mathbf{x}^n]^T$
Observation matrix: $\mathbf{Z} = [\mathbf{z}^1 \; \ldots \; \mathbf{z}^n]^T$

Training Set

Basis vector evaluated at new point

Correlation vector between training points and new point

Predictive mean

$$\hat{\mathbf{z}}(\mathbf{x}) = \mathbf{f}(\mathbf{x})^T \boldsymbol{\beta}^* + \mathbf{r}(\mathbf{x}\,|\,\mathbf{X})^T \mathbf{R}(\mathbf{X})^{-1}(\mathbf{Z} - \mathbf{F}(\mathbf{X})\boldsymbol{\beta}^*)$$

$$\boldsymbol{\beta}^* = \left[\mathbf{F}(\mathbf{X})^T \mathbf{R}(\mathbf{X})^{-1}\mathbf{F}(\mathbf{X})\right]^{-1} \mathbf{F}(\mathbf{X})^T \mathbf{R}(\mathbf{X})^{-1}\mathbf{Z}$$

Basis matrix with basis functions evaluated over all training points

Correlation matrix for all training points

Jia, G. and A.A. Taflanidis (2013). “Kriging metamodeling for approximation of high-dimensional wave and surge responses …”. *Computer Methods in Applied Mechanics and Engineering*, 261-262, 24-38.

Jia, G., Taflanidis, A.A., Nadal-Caraballo, N.C., Melby, J.A., Kennedy, A.B., Smith, J.M., (2015). Natural Hazards.

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Predictive variance (for each output)

$$\sigma_i^2(\mathbf{x}\,|\,\mathbf{X}) = \tilde{\sigma}_i^2[1 + \mathbf{u}(\mathbf{x}\,|\,\mathbf{X})^T\{\mathbf{F}(\mathbf{X})^T\mathbf{R}(\mathbf{X})^{-1}\mathbf{F}(\mathbf{X})\}^{-1}\mathbf{u}(\mathbf{x}\,|\,\mathbf{X}) - \mathbf{r}(\mathbf{x}\,|\,\mathbf{X})^T\mathbf{R}(\mathbf{X})^{-1}\mathbf{r}(\mathbf{x}\,|\,\mathbf{X})]$$

$$\text{where } \mathbf{u}(\mathbf{x}\,|\,\mathbf{X}) = \mathbf{F}(\mathbf{X})^T\mathbf{R}(\mathbf{X})^{-1}\mathbf{r}(\mathbf{x}\,|\,\mathbf{X}) - \mathbf{f}(\mathbf{x})$$

$$\text{process variance: } \tilde{\sigma}_i^2 = 1/n\sum_{h=1}^{n}\rho_{hi}^{\ 2}$$

ρ_{hi} elements of $\boldsymbol{\rho} = \mathbf{C}(\mathbf{X})^{-1}(\mathbf{Z} - \mathbf{F}(\mathbf{X})\boldsymbol{\beta}^*)$; $\mathbf{C}(\mathbf{x})$ Cholesky factorization of $\mathbf{R}(\mathbf{x})$

Hyper-parameter optimization

weight for different storms

Maximum Likelihood Estimation (MLE)

$$\mathbf{s}^* = \arg\min_{\mathbf{s}} \left[\left|\mathbf{R}(\mathbf{x})\right|^{\frac{1}{n}} \sum_{i=1}^{n_z} \gamma_i \tilde{\sigma}_i^2 \right] = \arg\min_{\mathbf{s}} \left[\left|\mathbf{R}(\mathbf{x})\right|^{\frac{1}{n}} \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h {\rho_{hi}}^2 \right]$$

weight for different outputs

outputs

storms

Leave-one out cross validation (LOOCV)

$$\mathbf{s}^* = \arg\min_{\mathbf{s}} H_m(\mathbf{s})$$

weight for different storms

$$H_m(\mathbf{s}) = \frac{1}{n_z n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h e_{hi}^2$$

outputs

storms

Can emphasis be given to specific observations (storms)?

Adaptive Design of Experiments

$$\mathbf{x}^{*}_{new} = \arg\min_{\mathbf{x}_{new}\in D} IMSE(\mathbf{X},\mathbf{x}_{new}) = \arg\min_{\mathbf{x}_{new}\in D} \int_{X^I} \varphi(\mathbf{x}) q(\mathbf{x}\,|\,\mathbf{X},\mathbf{x}_{new}) d\mathbf{x}$$

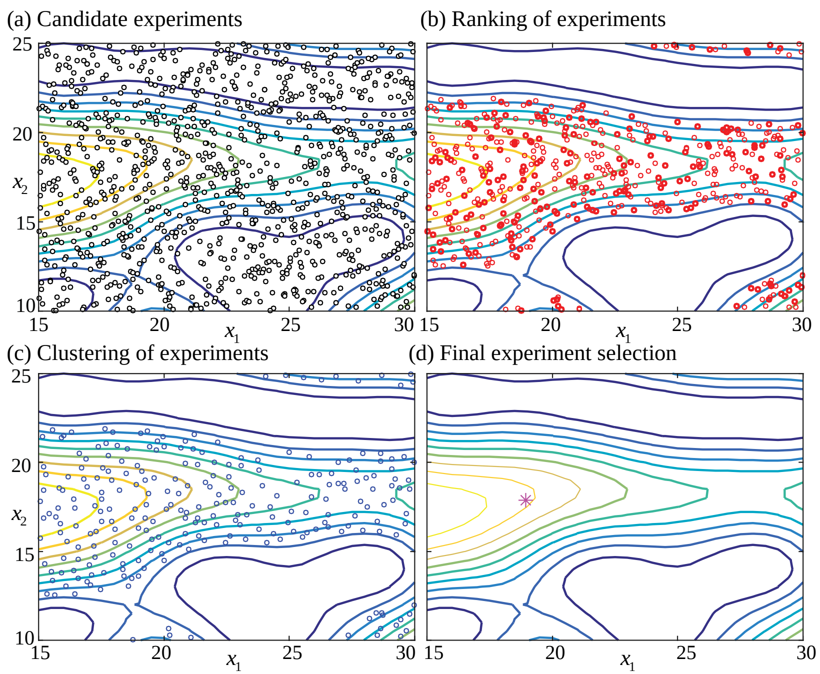
Monte Carlo

Weights

Normalized Predictive Variance

Initial sample

Experiments retained after 50% ranking based on variance



Experiments retained after 50% clustering

Final new optimal experiment after minimization of IMSE -> x_{new}

Contours of normalized variance

Bulk Surrogate Training
Coos Bay, OR

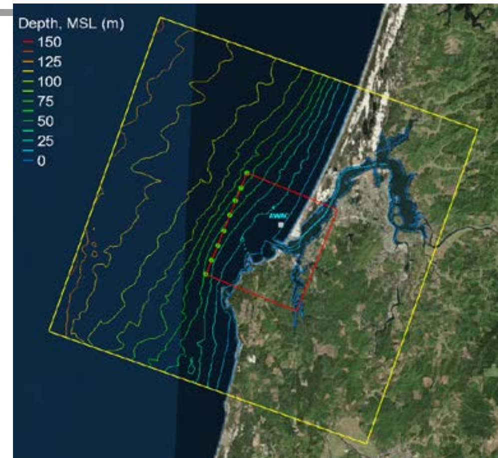
Inputs

- **Forcing**, input vector **x**
  - Offshore Wave Height H_{m0} (12 values from 1 to 15 m)
  - Offshore Peak Period T_p (8 values from 8 to 22 sec)
  - Offshore Mean Wave Direction (5 values from 220 to 240 deg)
  - Nearshore Total Water Level (9 values from -1.5 to 2.5 m, MSL)
  - 4320 Training events are synthetic

Outputs

- **Response:**
  - Nearshore Wave Height H_{m0}
  - Nearshore Peak Period T_p
  - Nearshore Mean Wave Direction
- All events transformed to nearshore using **CMS-Wave**

CMS-Wave Modeling
Coos Bay, OR

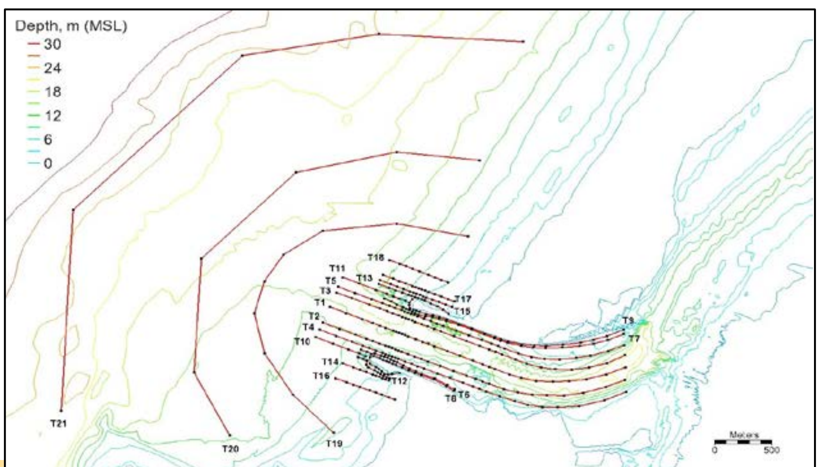


Parent Grid: 32 km x 32 km

Child Grid: 9.2 km x 10.3 km

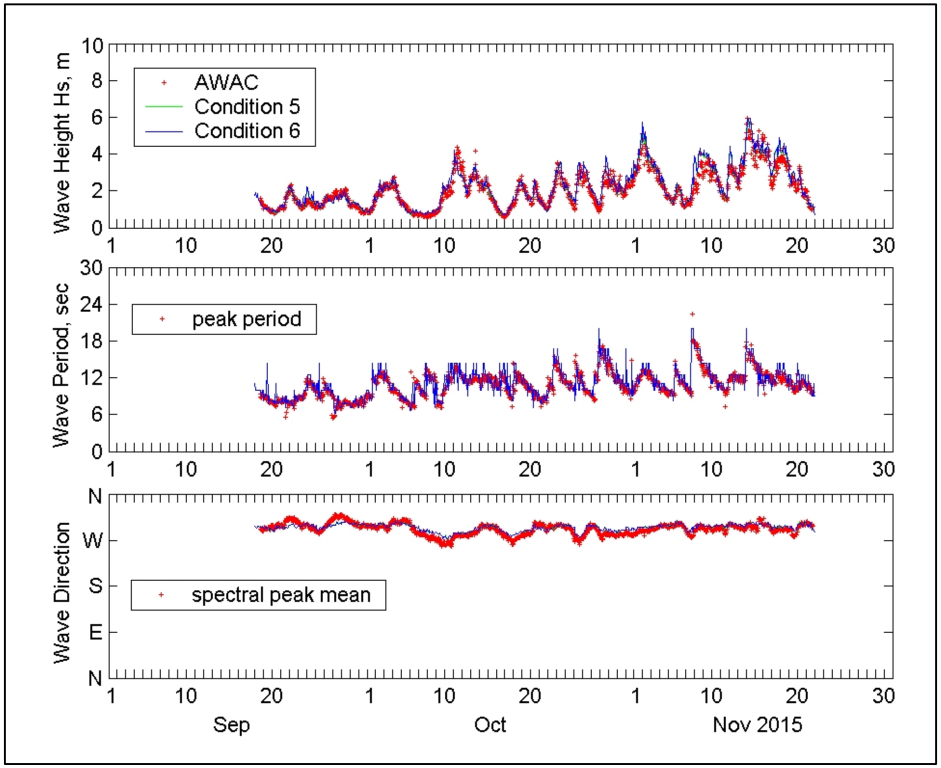
Forced by WIS station on seaward edge of parent grid

Validated with buoy 46229 and nearshore AWAC gage



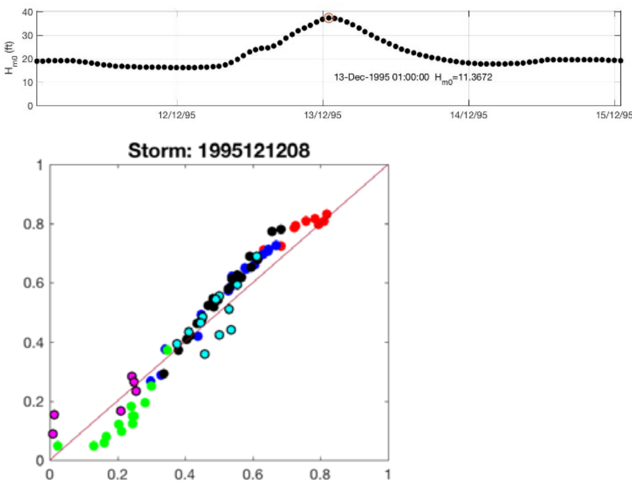
CMS-Wave Validation

	Mean	Bias	RMSE
H_{m0}, m	2.21	0.11	0.23
T_p, s	11.2	0.27	1.07
Dir, deg	293	3.2	7.4

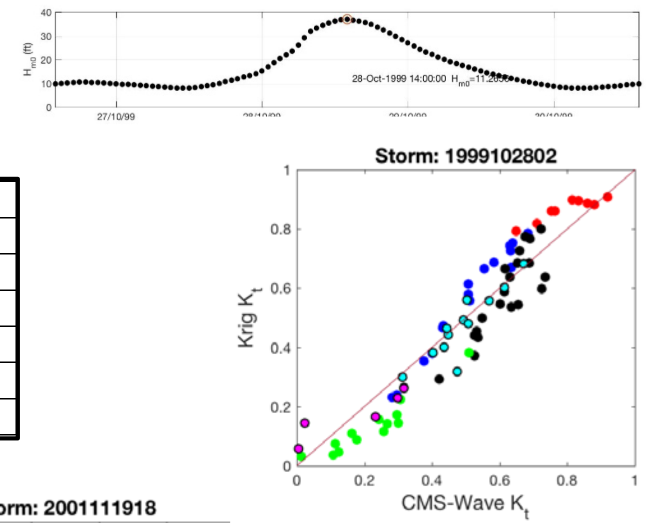


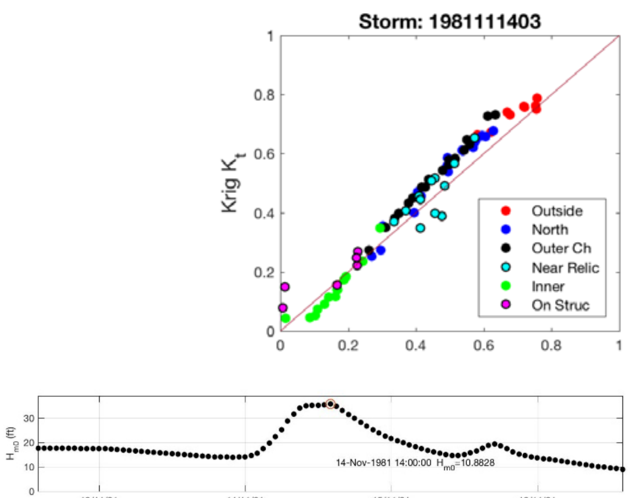
Ref: Lin et al. ICCE 2018

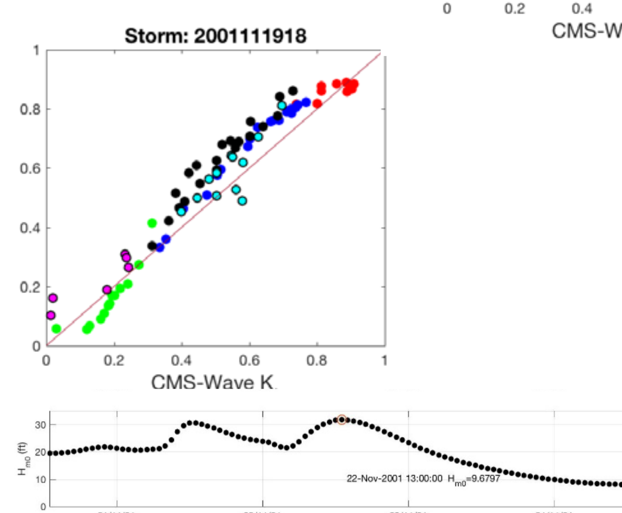
Surrogate Validation
WIS 83032, 4 of 5 top storms



Icon	Description
	Outside inlet in deeper water
	North of jetty
	Outer Channel
	Near relic structure head
	Inner channel
	On submerged relic structure head

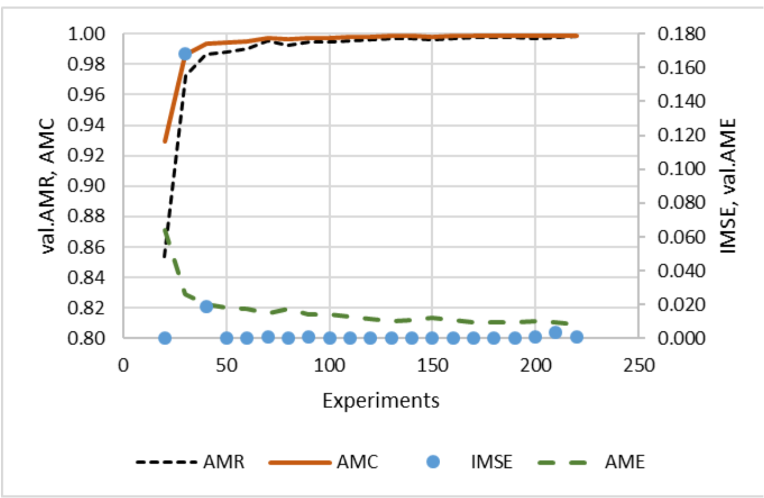


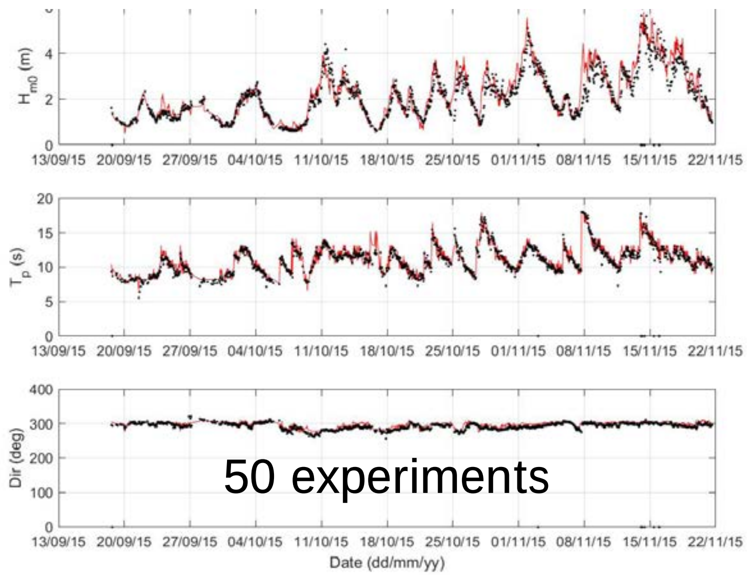




Adaptive Design of Experiments

- Select initial set of experiments as random input vector **x** (20)
- Compute normalized predictive variance q
- Rank based on variance and select subset with highest variance
- Reduce set based on clustering
- Compute incremental set of 10 experiments by minimizing IMSE





Conclusions

- Accurate risk assessment requires high fidelity modeling which is resource demanding
- Surrogates promote efficient yet accurate computations
- Adaptive DOE can dramatically reduce number of required simulations
- Applied at Coos Bay, OR for jetty life cycle probabilistic design and assessment
- Please see Victor Gonzalez pres., Fri, 0930