Enhanced Decision Support for Resilience to Natural hazards at Multiple Scales

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Fact: global urbanization trends
Climate vulnerability

![Map showing climate vulnerability rankings]
Seismic vulnerability
FACT: Between 2000 and 2050, we will double the population exposed to cyclones and earthquakes
Working across multiple scales

**REDUCE DISASTER RISK & ENHANCE RESILIENCE:**
- PLANNING DECISION SUPPORT
- STRENGTHENING HOUSING MARKETS

**PROMOTE RESILIENT & SUSTAINABLE BUILDING DESIGN:**
- POST-DISASTER RECONNAISSANCE
- ENHANCED DESIGN TOOLS
- HAZARD RESILIENT HOUSING

**ENCOURAGE & INCENTIVIZE RESILIENCE-ENHANCING DECISIONS**

Using Data

PLANNERS

DESIGNERS

OWNERS
Real-time risk assessment
Hurricane risk assessment fundamentals

Simplified parameterization of hurricane track

- Landfall location $x_o$
- Heading direction $\theta$
- Central pressure deficit $\Delta p$
- Forward speed $v_f$
- Radius of maximum winds $R_{mw}$

History prior to landfall is addressed by selecting appropriately the hurricane track (based on historical data)
Computational models for surge estimation

SLOSH model (computational efficiency, low accuracy)

- Established NOAA approach
- Large errors at shallow waters (where it matters!)

  - Simulation of each hurricane scenario → 2000-4000 CPU hours

ADCIRC (high accuracy, large computational burden)

- High fidelity model, with numerical grid having millions of nodes and elements
- Coupled surge/wave/current simulations and ability to provide diverse outputs
- Requires large degree of competency
Hurricane risk assessment using surrogates

Surrogate modeling

- Regional flood studies provide databased of ADCIRC high-fidelity runs
- Exploit them to develop rapid risk assessment tools

Hurricane simulation database (flood studies)
New prediction (surrogate model)
NACCS database I

- Database of 595 storms developed based on JPM-OS (joint probability method optimal sampling)

- 4 different angles of approach

- 89 different tracks

- Reference landfall location defined as 200 km away from coast
NACCS database II

- Database developed based on JPM-OS (joint probability method optimal sampling)
- 4 different angles of approach
- 89 different tracks
- Reference landfall location defined as 200 km away from coast
- Remaining characteristics varied based on discrete values
High-dimensional output

- Large dimension of output $z$ (few thousands) that stems from need to
  - calculate responses at different locations over coastal grid
  - calculate responses at different time instances

Solution: implement principal component analysis to reduce the dimension of output


- Matrix need to be kept in memory are large
- Impractical to develop different surrogate models
- Characteristics of optimal surrogate models for the different outputs can be different, so implementation of a single one for all outputs can reduce accuracy for some
High-dimensional output

- Large dimension of output $z$ (few thousands) that stems from need to
  - calculate responses at different locations over coastal grid
  - calculate responses at different time instances

- Initial output over 18,000 save points
- Memory savings of over 90%

Coefficient of Determination
Kriging implementation I

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

Experiment matrix: \( X = [x^1 \ldots x^n]^T \in \mathbb{R}^{n \times n_x} \)

Observation matrix: \( Z = [z^1 \ldots z^n]^T \in \mathbb{R}^{n \times n_z} \)

\( R(x',x^n|s) \): correlation function with hyper-parameters \( s \)
\( f(x) \): basis (trend) functions

\[ z(x) = f(x)^T \beta + n(x) \]
\[ z_i(x) \sim N(\hat{z}_i(x), \sigma_i(x)) \]

Predictive mean
\[ \hat{z}(x) = f(x)^T \beta^* + r(x \mid X)^T R(X)^{-1} (Z - F(X)\beta^*) \]
\[ \beta^* = \left[ F(X)^T R(X)^{-1} F(X) \right]^{-1} F(X)^T R(X)^{-1} Z \]

Basis vector evaluated at new point
Correlation vector between training points and new point
Correlation matrix for all training points
Basis matrix with basis functions evaluated over all training points
Kriging implementation II

$n_x$: input dimension (hurricane characteristics)

$n_z$: output dimension (surge response at different locations)

$n$: number of experiments (storms in database)

Experiment matrix: $X = [x_1 \ldots x^n]^T \in \mathcal{R}^{n \times n_x}$

Observation matrix: $Z = [z_1 \ldots z^n]^T \in \mathcal{R}^{n \times n_z}$

Predictive variance (for each output)

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

where $u(x \mid X) = F(X)^T R(X)^{-1} r(x \mid X) - f(x)$

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

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

$R(x',x^m|s)$: correlation function with hyper-parameters $s$

$f(x)$: basis (trend) functions

$z(x) = f(x)^T \beta + n(x)$

$z_i(x) \sim N(\hat{z}_i(x), \sigma_i(x))$

Independent of observations (dependent on correlation and basis functions)
Hyper-parameter optimization

- Maximum Likelihood Estimation (MLE)
  \[ s^* = \arg\min_s \left[ |R(x)|^{\frac{1}{n}} \sum_{i=1}^{n_z} \gamma_i \tilde{\sigma}_i^2 \right] = \arg\min_s \left[ |R(x)|^{\frac{1}{n}} \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} \rho_{hi}^2 \right] \]
  weight for different outputs

- Leave-one out cross validation (LOOCV)
  \[ s^* = \arg\min_s H_m(s) \]
  \[ H_m(s) = \frac{1}{n_z n} \sum_{i=1}^{n_z} \sum_{h=1}^{n} e_{hi}^2 \]
  Squared Error (for each training points) between actual observations and metamodel observations if training point was removed from database

Closed form solution:
\[ e_{hi}^2 = g_{hi} / c_{hh} \]
\[ c_{hh} \text{ diagonal elements of } R(x), \ g_{hi} \text{ elements of } g = R(X)^{-1}(Z - F(X)\beta^*) \]
Hyper-parameter optimization: prioritizing storms with specific characteristics

- Maximum Likelihood Estimation (MLE)
  \[ s^* = \arg \min_s \left[ \left| \mathbf{R}(\mathbf{x}) \right|^{\frac{1}{n}} \sum_{i=1}^{n_z} \gamma_i \bar{\sigma}_i^2 \right] = \arg \min_s \left[ \left| \mathbf{R}(\mathbf{x}) \right|^{\frac{1}{n}} \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} \rho_{hi}^2 \right] \]
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  \[ H_m(s) = \frac{1}{n_z n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} e_{hi}^2 \]
  outputs storms

Can emphasis be given to specific observations (storms)?
Hyper-parameter optimization: prioritizing storms with specific characteristics

- **Maximum Likelihood Estimation (MLE)**
  \[ s^* = \arg \min_s \left[ |R(x)|^{\frac{1}{n}} \sum_{i=1}^{n_z} \gamma_i \tilde{\sigma}_i^2 \right] = \arg \min_s \left[ |R(x)|^{\frac{1}{n}} \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h \rho_{hi}^2 \right] \]
  weight for different outputs
  weight for different storms

- **Leave-one out cross validation (LOOCV)**
  \[ s^* = \arg \min_s H_m(s) \]
  \[ H_m(s) = \frac{1}{n_z n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h e_{hi}^2 \]
  weight for different storms
  outputs
  storms

*Can emphasis be given to specific observations (storms)?
Metamodel accuracy II (Time-dependent outputs)


![Graphs showing storm surge predictions](chart.png)
Storm selection I

\[ IMSE(X) = \int_{\mathcal{X}} \varphi(x) q(x) \, dx \]

existing database

weight function over integration domain

Predictive variance (ignoring process variance)

\[ \sigma_i^2(x \mid X) = \tilde{\sigma}_i^2 \left[ 1 + u(x \mid X)^T \{ F(X)^T R(X)^{-1} F(X) \}^{-1} u(x \mid X) - r(x \mid X)^T R(X)^{-1} r(x \mid X) \right] \]
Storm selection II

\[
IMSE(X, x_{new}) = \int_{x^I} \varphi(x) q(x | X, x_{new}) dx
\]

existing database

new storm

\[
q(x | X, x_{new}) = 1 - r(x | X, x_{new})^T R(X, x_{new})^{-1} r(x | X, x_{new})
\]

\[
+ u(x | X, x_{new})^T \{F(X, x_{new})^T R(X, x_{new})^{-1} F(X, x_{new})\}^{-1} u(x | X, x_{new})
\]

\[q(x | X)\]

\[q(x | X, x_{new})\]
Storm selection II

\[
IMSE(X, x_{\text{new}}) = \int_{x'} \phi(x) q(x | X, x_{\text{new}}) dx
\]

existing database \quad new storm

\[
q(x | X, x_{\text{new}}) = 1 - r(x | X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x | X, x_{\text{new}})
+ u(x | X, x_{\text{new}})^T \{F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}})\}^{-1} u(x | X, x_{\text{new}})
\]
Storm selection III

\[ IMSE(X, x_{\text{new}}) = \int_{X'} \varphi(x) q(x | X, x_{\text{new}}) \, dx \]

 existing database

 new storm

\[ q(x | X, x_{\text{new}}) = 1 - r(x | X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x | X, x_{\text{new}}) \]

\[ + u(x | X, x_{\text{new}})^T \left\{ F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}}) \right\}^{-1} u(x | X, x_{\text{new}}) \]

 new storm that provides best anticipated benefit

\[ x^*_{\text{new}} = \arg\min_{x_{\text{new}} \in D} IMSE(X, x_{\text{new}}) = \arg\min_{x_{\text{new}} \in D} \int_{X'} \varphi(x) q(x | X, x_{\text{new}}) \, dx \]
Optimization for storm selection I

\[ x_{\text{new}}^* = \arg \min_{x_{\text{new}} \in D} \text{IMSE}(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_{X^I} \varphi(x)q(x \mid X, x_{\text{new}})dx \]

\[ q(x \mid X, x_{\text{new}}) = 1 - r(x \mid X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x \mid X, x_{\text{new}}) \]

\[ + u(x \mid X, x_{\text{new}})^T \{F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}})\}^{-1} u(x \mid X, x_{\text{new}}) \]

\[ R(X, x_{\text{new}})^{-1} = \begin{bmatrix}
R(X)^{-1} + \frac{1}{\eta_{\text{new}}} r(x_{\text{new}} \mid X)r(x_{\text{new}} \mid X)^T R(X)^{-1} & -\frac{1}{\eta_{\text{new}}} R(X)^{-1} r(x_{\text{new}} \mid X) \\
-\frac{1}{\eta_{\text{new}}} r(x_{\text{new}} \mid X)^T R(X)^{-1} & \frac{1}{\eta_{\text{new}}} \end{bmatrix} \]

\[ \eta_{\text{new}} = 1 - r(x_{\text{new}} \mid X)^T R(X)^{-1} r(x_{\text{new}} \mid X) \]
\[ x_\text{new}^* = \arg\min_{x_\text{new} \in D} IMSE(X, x_\text{new}) = \arg\min_{x_\text{new} \in D} \int_{\mathbb{X}^I} \varphi(x)q(x \mid X, x_\text{new})dx \]

**Monte Carlo simulation**

Random search
with pre-selection
step based on
variance

- Create candidate experiments \( x_{\text{cand}} \) in \( D \)

\[
q(x \mid X, x_{\text{new}}) = 1 - r(x \mid X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x \mid X, x_{\text{new}}) \\
+ u(x \mid X, x_{\text{new}})^T \{F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}})\}^{-1} u(x \mid X, x_{\text{new}}) 
\]
Optimization for storm selection II

\[ x_{new}^* = \arg \min_{x_{new} \in D} IMSE(X, x_{new}) = \arg \min_{x_{new} \in D} \int_{X_t} \varphi(x)q(x \mid X, x_{new})dx \]

\[ q(x \mid X, x_{new}) = 1 - r(x \mid X, x_{new})^T R(X, x_{new})^{-1} r(x \mid X, x_{new}) + u(x \mid X, x_{new})^T \{ F(X, x_{new})^T R(X, x_{new})^{-1} F(X, x_{new}) \}^{-1} u(x \mid X, x_{new}) \]

- Create candidate experiments \( x_{cand} \) in \( D \)
- Keep only those experiments, \( x_{ret} \), with higher values of \( q(x_{cand} \mid X) \)

Monte Carlo simulation

Random search

with pre-selection

step based on variance
Optimization for storm selection II

\[ x_{\text{new}}^* = \arg \min_{x_{\text{new}} \in D} \text{IMSE}(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_{X} \varphi(x) q(x \mid X, x_{\text{new}}) dx \]

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- Create candidate experiments \( x_{\text{cand}} \) in \( D \)
- Keep only those experiments, \( x_{\text{ret}} \), with higher values of \( q(x_{\text{cand}} \mid X) \)
- Calculate updated variance and \( \text{IMSE}(X \mid x_{\text{ret}}) \) successively for each of the retained experiments

Monte Carlo simulation

Random search with pre-selection step based on variance
Optimization for storm selection II

\[ x_{new}^* = \arg \min_{x_{new} \in D} \text{IMSE}(X, x_{new}) = \arg \min_{x_{new} \in D} \int_{X^I} \varphi(x) q(x \mid X, x_{new}) \, dx \]

Monte Carlo simulation

Random search
with pre-selection
step based on
variance

- Create candidate experiments \( x_{\text{cand}} \) in \( D \)
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\[ q(x \mid X, x_{new}) = 1 - r(x \mid X, x_{new})^T R(X, x_{new})^{-1} r(x \mid X, x_{new}) + u(x \mid X, x_{new})^T \{ F(X, x_{new})^T R(X, x_{new})^{-1} F(X, x_{new}) \}^{-1} u(x \mid X, x_{new}) \]
Optimization for storm selection II

\[ x_{\text{new}}^* = \arg \min_{x_{\text{new}} \in D} \text{IMSE}(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_{X^T} \varphi(x)q(x \mid X, x_{\text{new}})dx \]

Monte Carlo simulation

\[ q(x \mid X, x_{\text{new}}) = 1 - r(x \mid X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x \mid X, x_{\text{new}}) \]
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Random search with pre-selection step based on variance

- Create candidate experiments \( x_{\text{cand}} \) in \( D \)
- Keep only those experiments, \( x_{\text{ret}} \), with higher values of \( q(x_{\text{cand}} \mid X) \)
- Calculate updated variance and \( \text{IMSE}(X \mid x_{\text{ret}}) \) successively for each of the retained experiments
Optimization for storm selection II

\[ x_{\text{new}}^* = \arg \min_{x_{\text{new}} \in D} IMSE(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_{X'} \phi(x)q(x | X, x_{\text{new}})dx \]

Random search with pre-selection step based on variance

- Create candidate experiments \( x_{\text{cand}} \) in \( D \)
- Keep only those experiments, \( x_{\text{ret}} \), with higher values of \( q(x_{\text{cand}} | X) \)
- Calculate updated variance and \( IMSE(X | x_{\text{ret}}) \) successively for each of the retained experiments
- Choose the one corresponding to minimum

\[ q(x | X, x_{\text{new}}) = 1 - r(x | X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x | X, x_{\text{new}}) + u(x | X, x_{\text{new}})^T \{ F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}}) \}^{-1} u(x | X, x_{\text{new}}) \]
Optimization for storm selection III

\[ x^*_{\text{new}} = \arg \min_{x_{\text{new}} \in D} IMSE(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_{X^I} \varphi(x)q(x \mid X, x_{\text{new}})dx \]

Monte Carlo simulation

Random search with pre-selection step based on variance

\[ q(x \mid X, x_{\text{new}}) = 1 - r(x \mid X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x \mid X, x_{\text{new}}) \]

\[ + u(x \mid X, x_{\text{new}})^T \{ F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}}) \}^{-1} u(x \mid X, x_{\text{new}}) \]

Evaluate response for new experiment and optimize hyper-parameters
Optimization for storm selection III

\[ x_{\text{new}}^* = \arg \min_{x_{\text{new}} \in D} \text{IMSE}(X, x_{\text{new}}) = \arg \min_{x_{\text{new}} \in D} \int_X \varphi(x) q(x \mid X, x_{\text{new}}) \, dx \]

Monte Carlo simulation

Random search

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\[ q(x \mid X, x_{\text{new}}) = 1 - r(x \mid X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} r(x \mid X, x_{\text{new}}) + u(x \mid X, x_{\text{new}})^T \{ F(X, x_{\text{new}})^T R(X, x_{\text{new}})^{-1} F(X, x_{\text{new}}) \}^{-1} u(x \mid X, x_{\text{new}}) \]

Evaluate response for new experiment and optimize hyper-parameters
Increase of size of database improves accuracy
Smart selection of storms further improves accuracy
Criteria for storm selection important

Utilizing smart selection, accurate risk assessment (compared to JPM-OS) can be achieved with reduced number of storms compared to the initial 595.
Addressing storm intensification I

Storm intensification (impact of climate change) is a practical concern.

*Can we explicitly train a surrogate model to provide predictions for future higher intensity storms?*
Addressing storm intensification II

Storm intensification (impact of climate change) is practical concern.

*Can we explicitly train surrogate model to provide predictions for future higher intensity storms*

\[
(MLE) \ s^* = \arg \min_s \left[ |R(x)| \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h \rho_{hi} \right]^{2}
\]

\[
(LOOCV) \ s^* = \arg \min_s \frac{1}{n_z n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h e_{hi}
\]

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<th>weights $w_h = 1$</th>
<th>MLE</th>
<th>LOOCV</th>
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<td>$R^2$ for extrapolation</td>
<td>0.811</td>
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Addressing storm intensification II

Storm intensification (impact of climate change) is a practical concern.

*Can we explicitly train a surrogate model to provide predictions for future higher intensity storms?*

\[
(MLE) \ s^* = \arg \min_s \left[ |R(x)| \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n} w_h \rho_{hi}^2 \right]
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Addressing storm intensification III

Storm intensification (impact of climate change) is practical concern.

*Can we explicitly train surrogate model to provide predictions for future higher intensity storms*

(MLE) \( s^* = \arg \min_s \left[ |R(x)| \frac{1}{n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n_w} w_h \rho_{hi}^2 \right] \)

(LOOCV) \( s^* = \arg \min_s \frac{1}{n_z n} \sum_{i=1}^{n_z} \gamma_i \sum_{h=1}^{n_w} w_h e_{hi} \)

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Addressing storm intensification IV

Storm intensification (impact of climate change) is a practical concern.

*Can we explicitly train surrogate model to provide predictions for future higher intensity storms*

\[
\text{(MLE) } s^* = \arg \min_{s} \left[ |R(x)|^\frac{1}{n} \sum_{i=1}^{n} \gamma_i \sum_{h=1}^{n} w_h \rho_{hi}^2 \right]
\]

\[
\text{(LOOCV) } s^* = \arg \min_{s} \frac{1}{n_x n} \sum_{i=1}^{n_x} \gamma_i \sum_{h=1}^{n} w_h e_{hi}
\]

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Addressing storm intensification V

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**NJcoast**

*NJcoast* is a platform for geospatial data analysis that includes custom storm simulations through the *Storm Hazard Projection Tool*.

Platform incorporates dozens of GIS layers mapping shoreline and topographic features, infrastructure elements, parcels, critical facilities, and transportation networks across the State of New Jersey.
NJcoast
Working across multiple scales

REDUCE DISASTER RISK & ENHANCE RESILIENCE:
- PLANNING DECISION SUPPORT
- STRENGTHENING HOUSING MARKETS

PROMOTE RESILIENT & SUSTAINABLE BUILDING DESIGN:
- POST-DISASTER RECONNAISSANCE
- ENHANCED DESIGN TOOLS
  HAZARD RESILIENT HOUSING

ENCOURAGE & INCENTIVIZE RESILIENCE-ENHANCING DECISIONS

“Challenges/Need” with/for Data
Community resilience

COMMUNITY RESILIENCE TO NATURAL HAZARDS

METRICS

NETWORKS

DESCRIPTORS

DISRUPTORS

INTERCONNECTED SYSTEM

INTEGRATED SFSE SYSTEM

ISOLATED SYSTEM

COMPONENT

CIVIL INFRASTRUCTURE

NATURAL HAZARDS
FRAMEWORK OVERVIEW:
-- Multi-hazard (probabilistic) damage assessment
-- Different consequence metrics
  -- Repair cost (direct losses)
  -- Downtime (resilience quantification)
  -- Embodied energy of repairs

-- Automated workflow that is based on practitioner tools so it can be interface with existing design firm approaches

-- Assembly-based methodology for vulnerability quantification provides designers with the granularity to make well-informed design decisions

-- Challenge: data
Learning from disasters

- Risk Communication
- Policy
- Disaster Risk Reduction
- Computational Simulation
- Practice
- Post-Event Recon
- Learning from Disasters
- Resilient Design
CASE STUDY: PORT SALUT, Haiti (Hurricane MATHEW)
Concluding thoughts

- *Computational simulation and uncertainty quantification (UQ) have to play a critical role in quantifying hazard risk/resilience.*

- *Computational statistics tools (machine learning & data science) provide unique opportunities to support enhanced short-term (emergency response) and long-term (planning) decision support.*

- Critical challenge is *lack of data* for proper consequence-quantification. This pertains to both the individual component level, and more importantly at community resilience level.

Thank You!