Integrated Probabilistic Framework for Rapid Hurricane-Risk Assessment

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Question

- How do you build a fast wave, surge, and run-up hurricane environment forecast that is based on high fidelity physics?
  - Deterministic and Stochastic
  - Integrates into forecast frameworks

Methods

- Parameterize storm characteristics with track/angle, landfall location, central pressure, size, forward speed
- Apply a Monte Carlo approach based on a large number of simulations
- Develop a data base of response functions using high fidelity – high cost models across the parameter set. These model runs are pre-run, stored and permanent.
- Develop a surrogate model approach that produces the response functions for the Monte Carlo approach and is based on the pre-computed high-fidelity simulations

Conclusions

- A probabilistic framework was developed for rapid hurricane risk estimation focusing on real time applications (during an approaching hurricane)

- Framework is based on a simplified parametric description of hurricane track. It combines high-fidelity model simulations (accuracy) along with response surface surrogate modeling (efficiency)

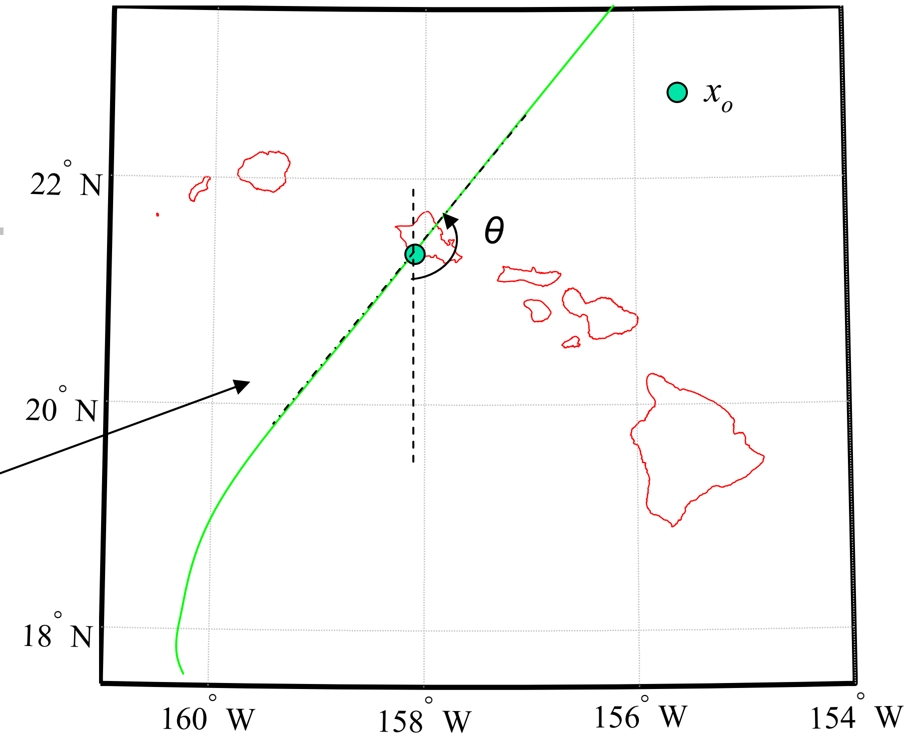
- It facilitates a highly efficient estimation of hurricane risk, through a stand-alone applet, and can provide critical information for emergency response managers

Hurricane Characterization

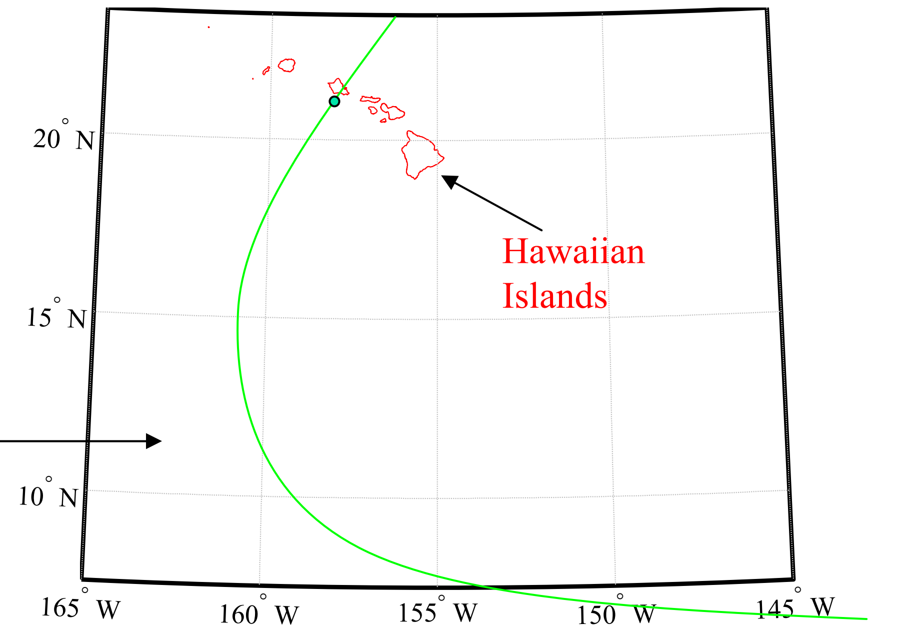
<u>Foundation of the approach:</u> Simplified parameterization of hurricane track

- **Track is described by its characteristics during final approach**
  - **Landfall location x_o**
  - **Angle of approach θ**
  - **Central pressure c_p (hurricane intensity)**
  - **Forward speed v_f**
  - **Radius of maximum winds R_{max}**

x

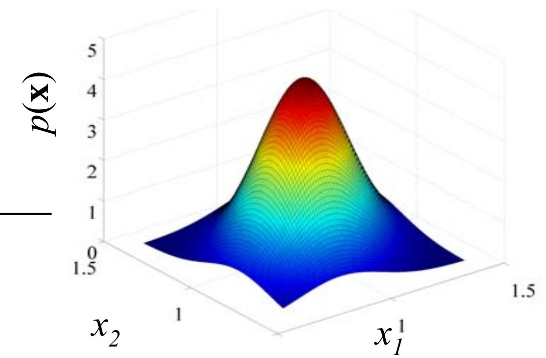


- **History prior to landfall is addressed by selecting appropriately the hurricane track (based on historical data)**



Hurricane Risk Quantification

Address the uncertainty in **x** through appropriate probability models $p(\mathbf{x})$



$$R = \int_X h[\mathbf{z}(\mathbf{x})]p(\mathbf{x})d\mathbf{x}$$

Hurricane Risk

h: Risk consequence measure ultimately defining risk

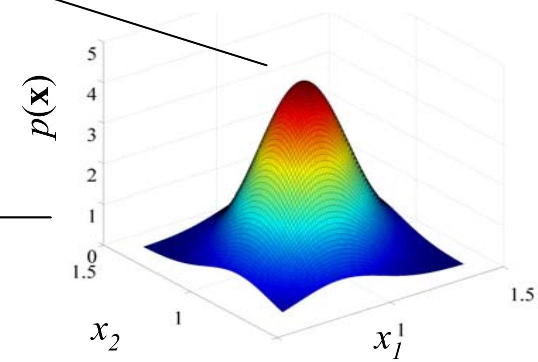
z: output of interest such as (a) significant wave height, (b) mean sea level (MSL) or (c) wave breakup level (WBL)

Hurricane Risk Quantification

Probability model $p(\mathbf{x})$

(i) For real time risk estimation (during an approaching hurricane) based on the predictions of the National Weather Service

(ii) For long term risk estimation based on historical data for characteristics and occurrence rates of hurricanes in the region



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Hurricane Risk Estimation

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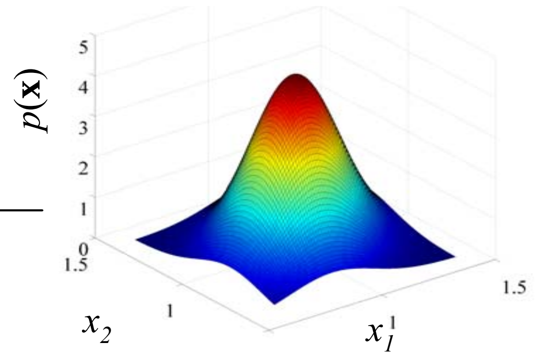


$$R = \int_X h[\mathbf{z}(\mathbf{x})]p(\mathbf{x})d\mathbf{x}$$

Hurricane Risk

Stochastic Simulation

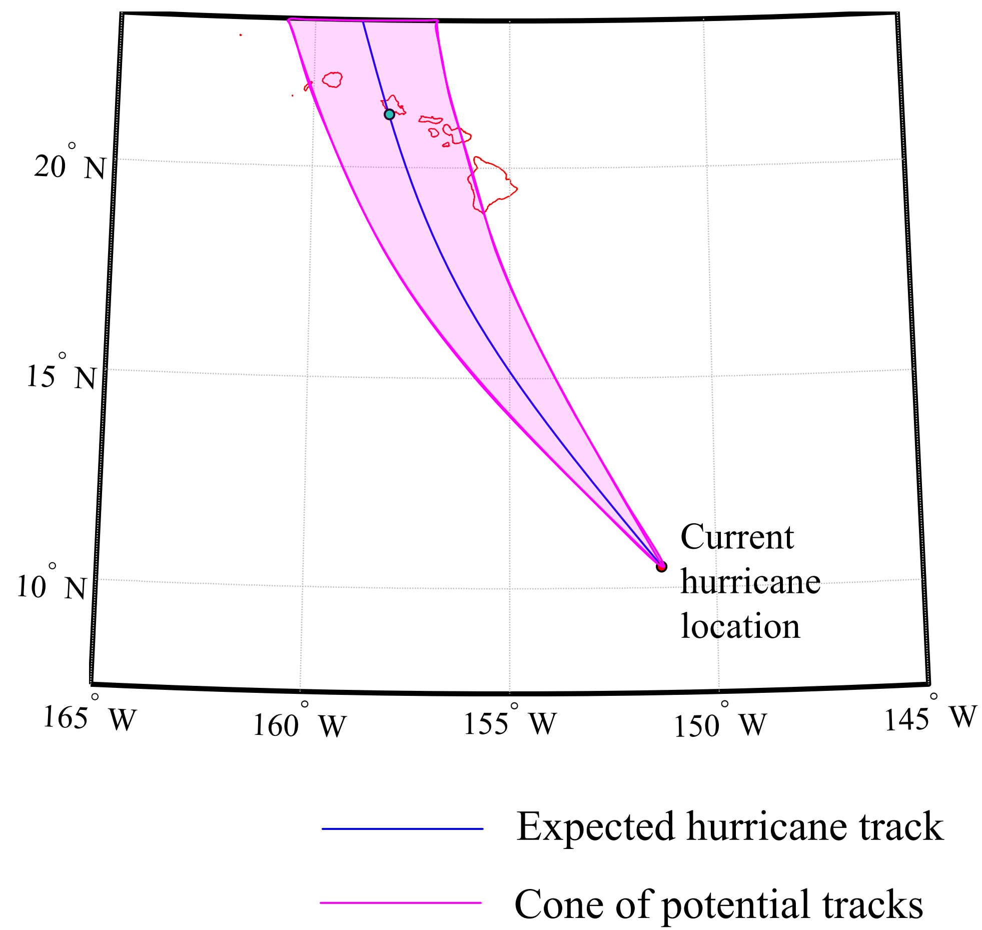
$$R \approx \frac{1}{N}\sum_{i=1}^{N} h[\mathbf{z}(\mathbf{x}_i)]; \quad \mathbf{x}_i \sim p(\mathbf{x})$$

No restriction on the complexity of the model used but requires a large number of evaluations, for different hurricane scenarios

Real-time Hurricane Risk Estimation

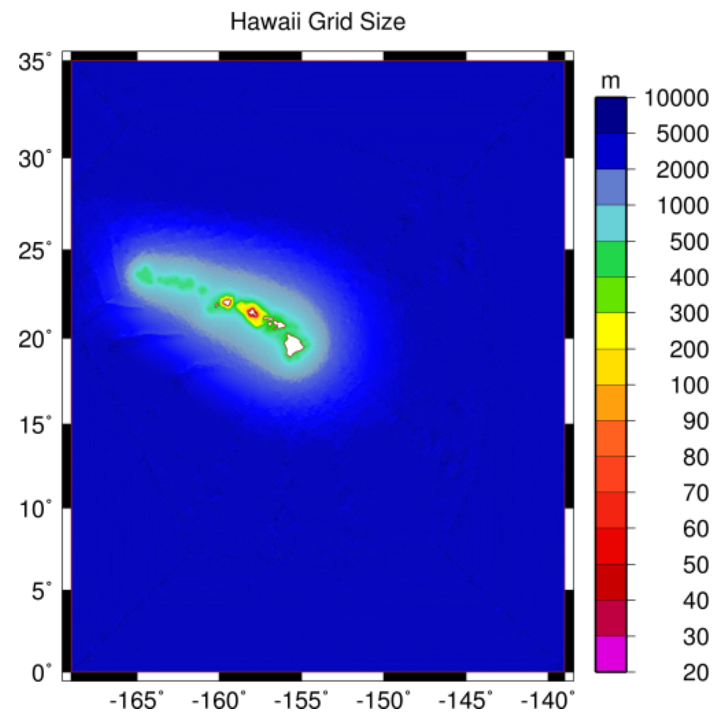
- During incoming hurricane the National Weather Service provides estimates for expected track and strength characteristics, along with prediction errors

- Goal: provide a fast prediction tool that can accurately estimate hurricane risk as soon as these predictions are provided



High Fidelity Model

- Domain incorporates all Hawaiian Islands and north central Pacific Ocean
- Fully incorporates high resolution features, channels, coral reefs and wave breaking zones
- 1,590,637 nodes, 3,527,785 elements
- ADCIRC+SWAN for estimating surge and wave action
- For Run up: Boussinesq modeling along one dimensional transects using the wave/surge information from SWAN/ADCIRC
- Very detailed numerical modeling but very computationally demanding



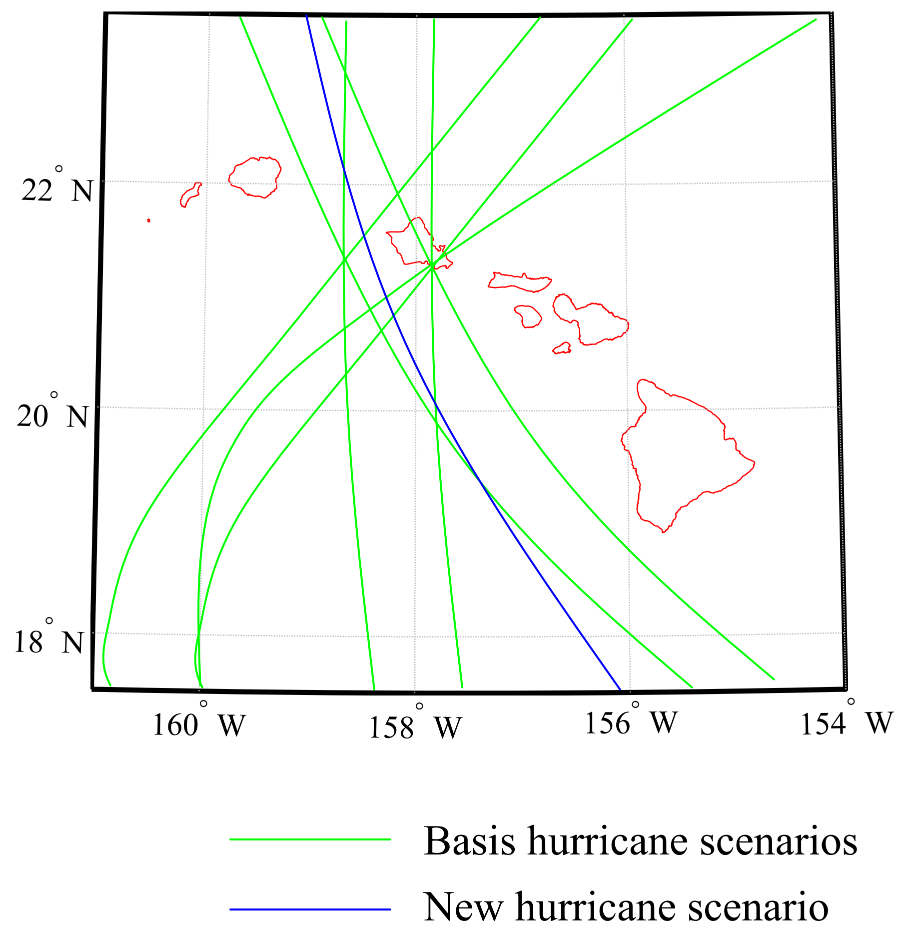
- **Simulation of each hurricane track (4 days prior to landfall and one day after) requires 2,000 CPU hours**

Surrogate Model

- Computational complexity of the adopted numerical models imposes a significant challenge for the risk assessment task, especially when needed to be performed in real time
- The solution is to develop a surrogate model to provide a simple, approximate input/output relationship, based on information from the high fidelity model. The surrogate model needs to
  - Be easy to evaluate
  - Provide efficiently information for *all* outputs of interest
  - Have easy to quantify and adjust accuracy

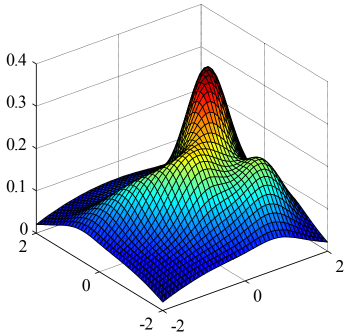
Hurricane Risk Estimation

- **Pre-run and store** a large suite of **basis hurricane scenarios** (using high-fidelity modeling) that cover expected range of future events for
  - Anticipated tracks and landfall locations
  - Rest of hurricane characteristics (central pressure, forward speed, radius of max winds)
- Based on basis scenarios predict **fast and accurately** the output for any **new** hurricane scenario through a surrogate model. Moving Least Squares (MLS) response surfaces used for this purpose



MLS Response Surface Approximation

Response surfaces: Approximate a function $f(\mathbf{x})$ through *NB* basis functions



Real Surface

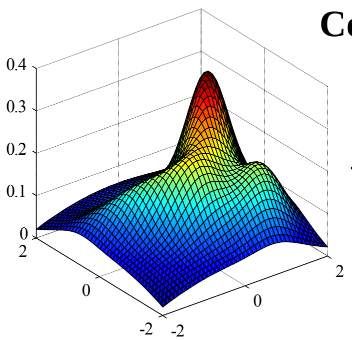
Coefficients for approximation

$$\hat{f}(\mathbf{x}) = \sum_{i=1}^{NB} b_i(\mathbf{x}) a_i\{\mathbf{x}\} = \mathbf{b}(\mathbf{x})^T \mathbf{a}\{\mathbf{x}\}$$

Basis functions

MLS Response Surface Approximation

Response surfaces: Approximate a function *f*(x) through *NB* basis functions



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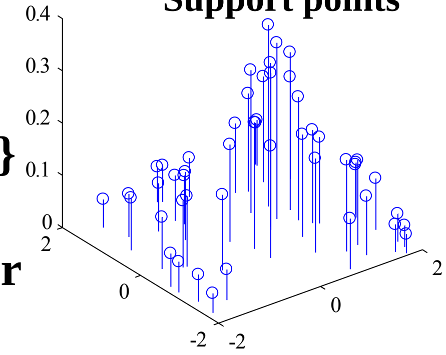
Basis functions

Calculate *f*(.) in *NS* support points, and use them to select a{.} by minimizing a weighted square error



Support points

Error over all support points

$$J_R\{\mathbf{x}\} = \sum_{I=1}^{NS} w\{\mathbf{x}\}[\hat{f}(\mathbf{x}_I) - f(\mathbf{x}_I)]^2$$
$$= \sum_{I=1}^{NS} w\{\mathbf{x}\}[\mathbf{b}(\mathbf{x}_I)^T \mathbf{a}\{\mathbf{x}_I\} - f(\mathbf{x}_I)]^2$$

weights

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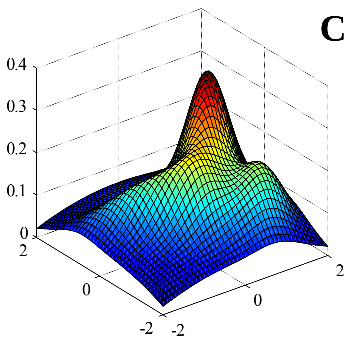

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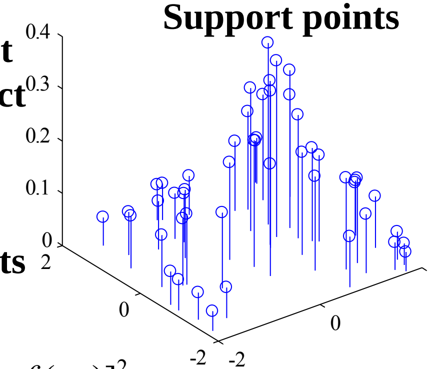

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$$= \sum_{I=1}^{NS} w\{\mathbf{x}\}[\mathbf{b}(\mathbf{x}_I)^T \mathbf{a}\{\mathbf{x}_I\} - f(\mathbf{x}_I)]^2$$

weights

Solution for a{.}

$$\hat{f}(\mathbf{x}) = \mathbf{b}^T(\mathbf{x}) \overbrace{\left[\mathbf{B}^T \mathbf{W}\{\mathbf{x}\} \mathbf{B}\right]^{-1} \mathbf{B}^T \mathbf{W}\{\mathbf{x}\} \mathbf{F}}^{\text{Solution for } \mathbf{a}\{.\}}$$

$$\mathbf{B} = [\mathbf{b}(\mathbf{x}_1) \ldots \mathbf{b}(\mathbf{x}_{NS})]^T \qquad \mathbf{F} = [f(\mathbf{x}_1) \ldots f(\mathbf{x}_{NS})]^T$$

$$\mathbf{W}\{\mathbf{x}\} = diag[w(d(\mathbf{x};\mathbf{x}_1)) \ldots w(d(\mathbf{x};\mathbf{x}_{NS}))]$$

Easy to evaluate (matrix manipulation only);

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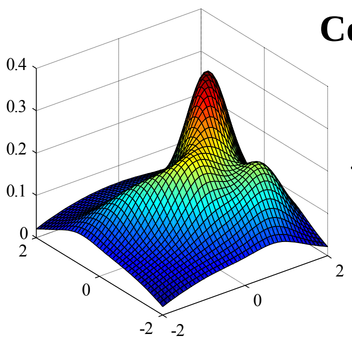
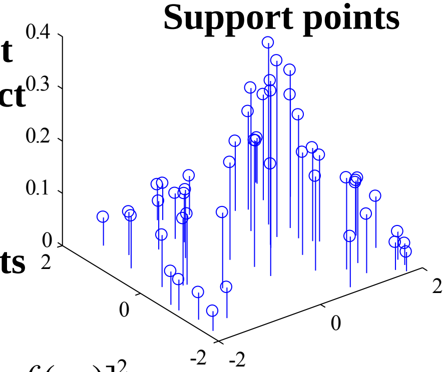
Basis functions



Real Surface

Calculate $f(.)$ in NS support points, and use them to select a{.} by minimizing a weighted square error

Support points



Error over all support points

$$J_R\{\mathbf{x}\} = \sum_{I=1}^{NS} w\{\mathbf{x}\}[\hat{f}(\mathbf{x}_I) - f(\mathbf{x}_I)]^2$$
$$= \sum_{I=1}^{NS} w\{\mathbf{x}\}[\mathbf{b}(\mathbf{x}_I)^T \mathbf{a}\{\mathbf{x}_I\} - f(\mathbf{x}_I)]^2$$

weights

Easy to evaluate (matrix manipulation only); and multiple outputs can be simultaneously addressed [only augmentation or matrices needed]

$$\hat{f}(\mathbf{x}) = \mathbf{b}^T(\mathbf{x}) \underbrace{\left[\mathbf{B}^T \mathbf{W}\{\mathbf{x}\}\mathbf{B}\right]^{-1} \mathbf{B}^T \mathbf{W}\{\mathbf{x}\}\mathbf{F}}_{\text{Solution for } \mathbf{a}\{.\}}$$

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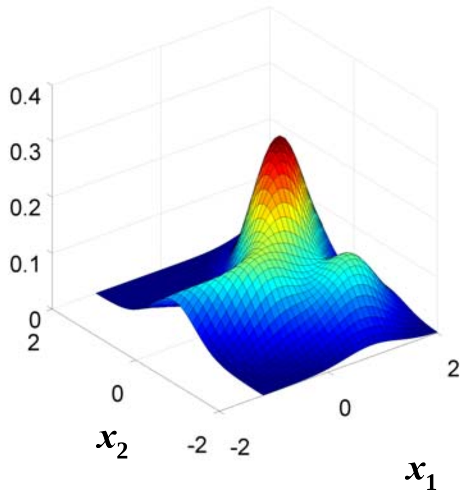
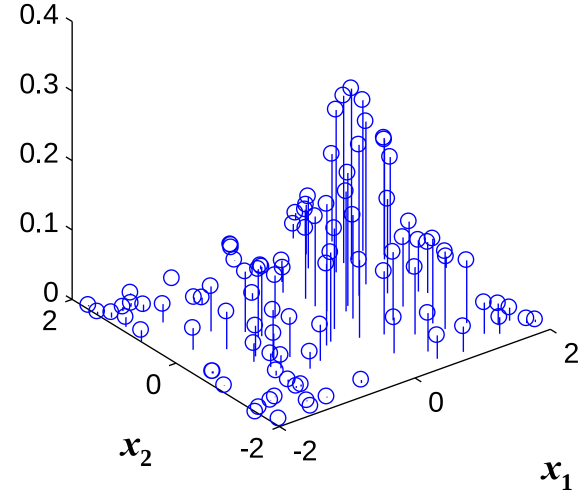
MLS Response Surface Approximation

$f(\mathbf{x})$



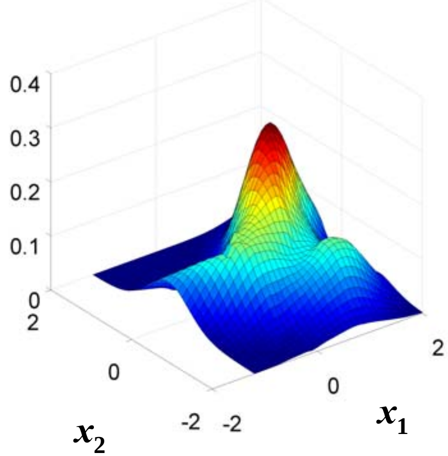
basis points



Response surfaces for quadratic basis functions

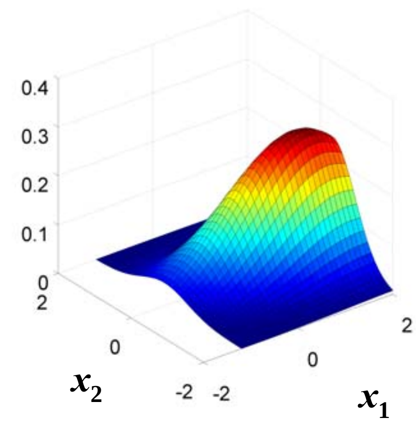
$\hat{f}(\mathbf{x})$

MLS



$\hat{f}(\mathbf{x})$

GLS



- **“Moving” characteristics of response surface are extremely important for efficient implementation. “Global” surfaces will in general perform poorly.** ***The parameters related to “moving” characteristics can be explicitly optimized to improve accuracy***

Response Surface Optimization

Surrogate model accuracy	Case			
	quadratic basis functions for x_o, θ, c_p and v_f and linear for R_m			Full quadratic function for all model parameters
	Case 1 Optimal response surface	**Case 2** common values are used for weighting function	**Case 3** No smart prioritization when interpolating within **x**	**Case 4** Sub-optimal response surface (optimal for specific basis functions)
Average error	2.31%	2.82%	4.54 %	2.93%

Different cases considered (for different characteristics of the moving lease squares); optimal configuration leads to significant improvement of average accuracy

Prediction Error

High fidelity model output

Prediction error

$$z_i = \hat{z}_i + \varepsilon_i$$

Response surface output

How can we explicitly consider accuracy in risk estimation?

Prediction Error

High fidelity model output

Prediction error

$$z_i = \hat{z}_i + \varepsilon_i$$

Response surface output

Can statistically characterize and incorporate in risk quantification framework; zero mean Gaussian random variable with standard deviation

$$\sigma_{\varepsilon_i} = \sqrt{\frac{1}{N_E}\sum_{p=1}^{N_E}\left(z_i(\mathbf{x}_p) - \hat{z}_i(\mathbf{x}_p)\right)^2}$$

Points selected for calibration of model and estimation of statistics for prediction error

Prediction Error

High fidelity model output

Prediction error

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Response surface output

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Points selected for calibration of model and estimation of statistics for prediction error

Risk: probability of exceeding some threshold

$$R_i = \int\int_{z_i>\beta_i} p(\mathbf{x})p(e_i)d\mathbf{x}de_i = \int_X\left[\int_{e_i>\beta_i-\hat{z}_i} p(e_i)de_i\right]p(\mathbf{x})d\mathbf{x}$$

$$= \int_X\left[\int_0^{\hat{z}_i-\beta_i} p(e_i)de_i\right]p(\mathbf{x})d\mathbf{x} = \int_X \boxed{\Phi\left[\frac{\hat{z}_i-\beta_i}{\sigma_{\varepsilon_i}}\right]} p(\mathbf{x})d\mathbf{x}$$

Can then directly incorporate error in analysis through appropriate definition of risk consequence measure

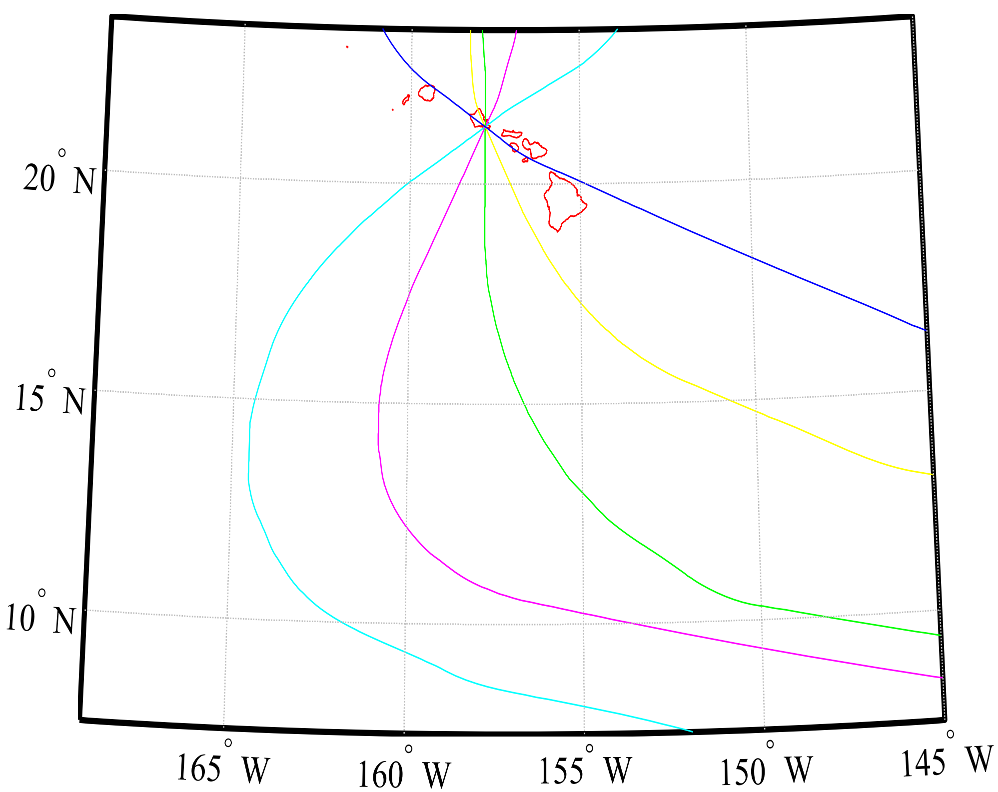
Basis Hurricane Scenarios

Landfall Location 1: 21.3° N 157.85° W

Angle of approach (track)

- 120°
- 150°
- 180°
- 210°
- 240°

For each track consider variation of rest characteristics



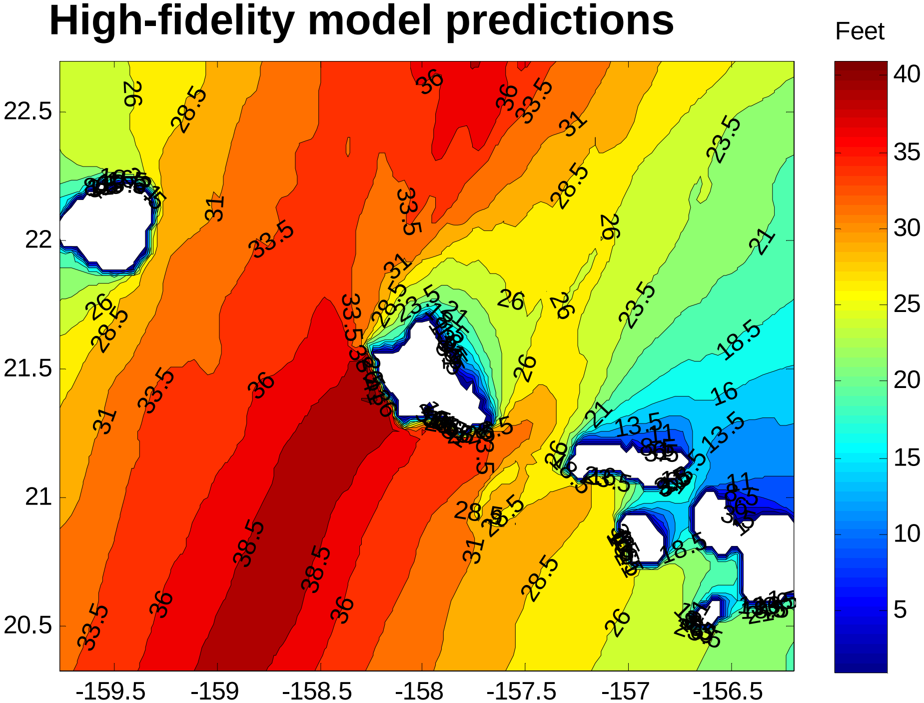
Central Pressure (mbar)	Forward Speed (knots)	Radius of max winds (km)
940	7.5	30
		60
	15	30
		60
	22.5	30
		60
955	7.5	30
		60
	15	30
		60
	22.5	30
		60
970	7.5	30
		60
	15	30
		60
	22.5	30
		60

Considering additional different landfall locations:

a suite of >600 model runs to represent the variety of storms that might impact Oahu

Comparison of surrogate modeling

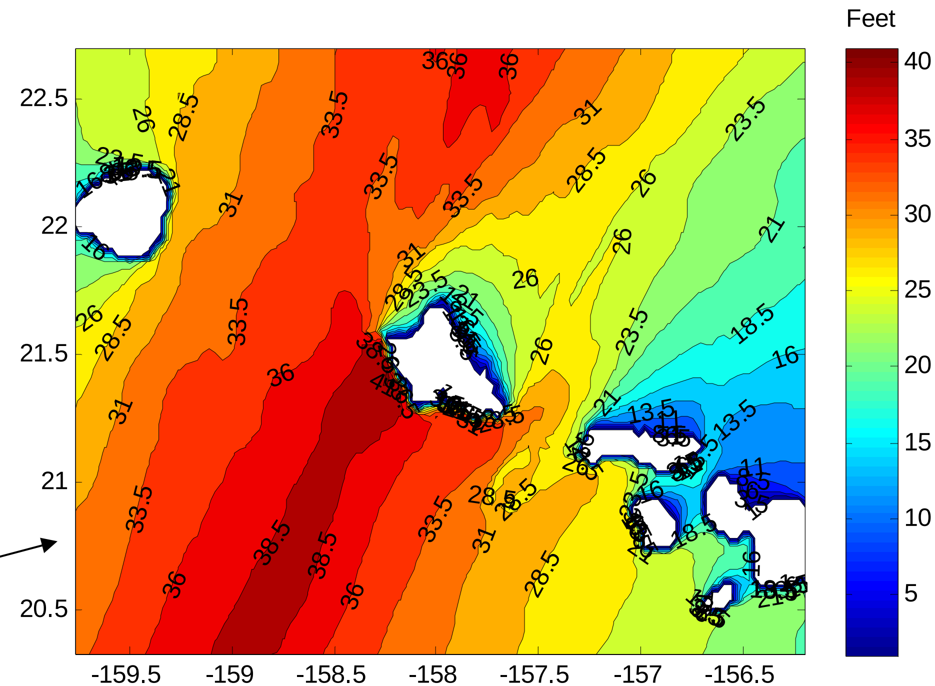
High-fidelity model predictions



2000 computational hours per scenario

Comparison of significant wave height around Hawaiian islands

Surrogate model predictions



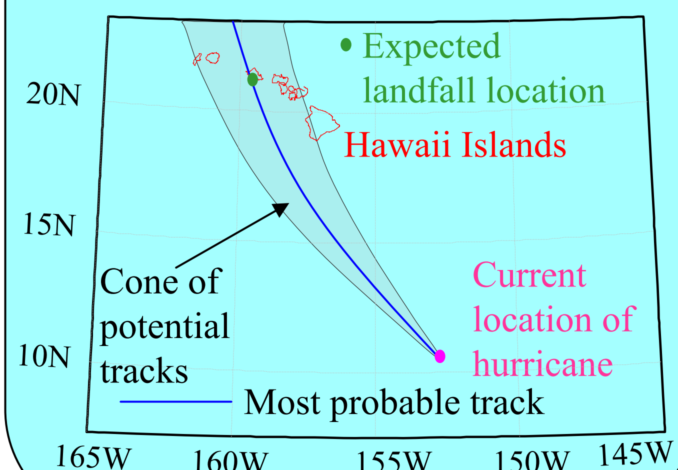
0.5 sec per scenario

Real Time Hurricane Risk Evaluation

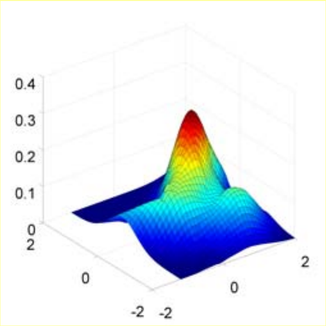
4 stochastic simulation

$$Risk = \frac{1}{N}\sum_{i=1}^{N} h[\mathbf{z}(\mathbf{x}_i)]$$

3 NWS: definition of probability distribution for hurricane characteristics $p(\mathbf{x})$



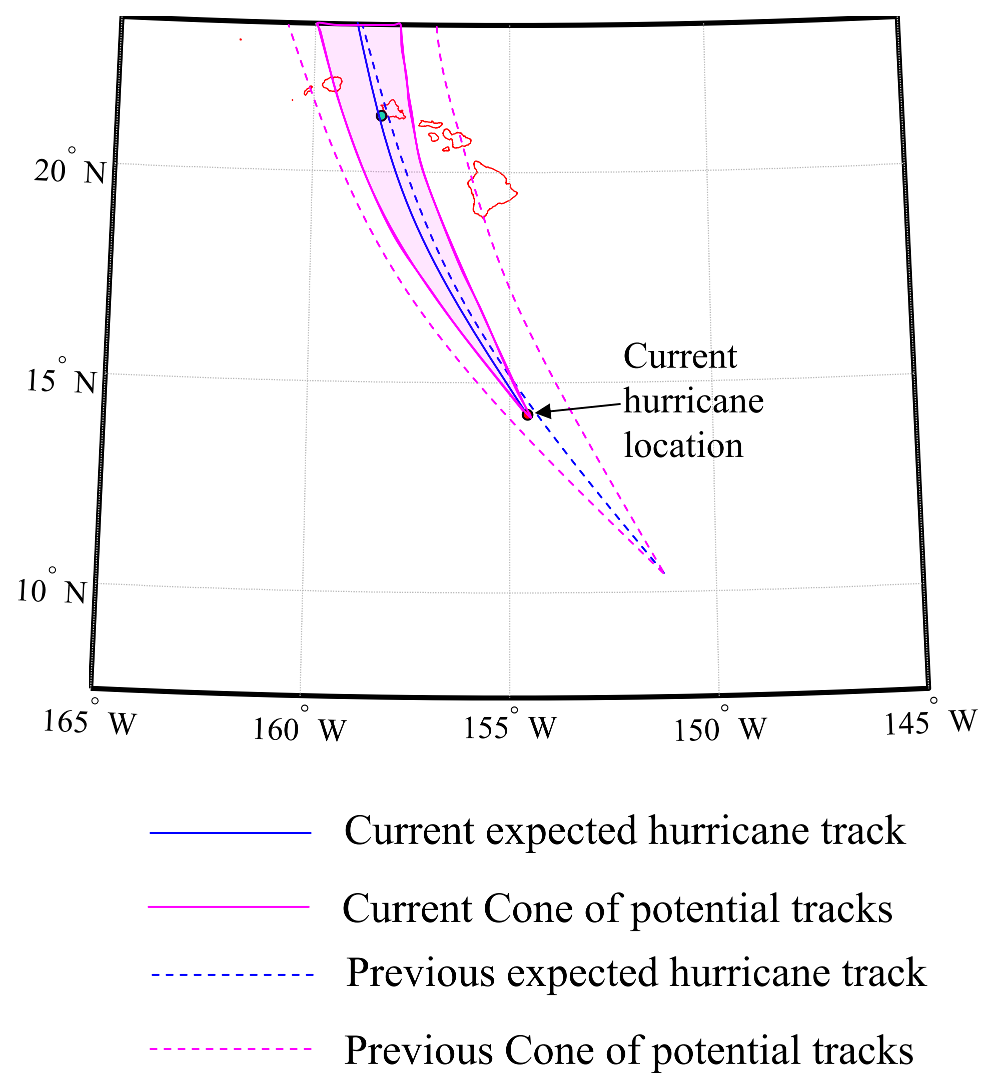
2 Built surrogate model based on available information



1 **Offline**: Evaluation of the high fidelity model, through high performance computing (store in memory all information)

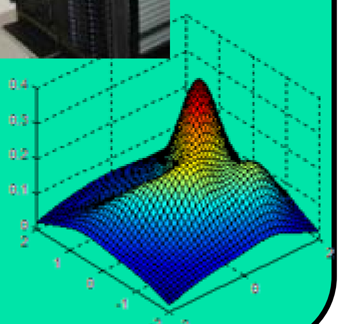
Hurricane Risk Estimation

- Based on surrogate model hurricane risk may be efficiently calculated
- As the hurricane gets closer and more reliable information is available, the evaluation may be updated
- The overall framework provides a dynamic and fast evaluation of the hurricane risk. This risk may be then used to assess consequences and decide on emergency responses



Automated Risk Assessment

High fidelity simulation + surrogate modeling + probabilistic tools



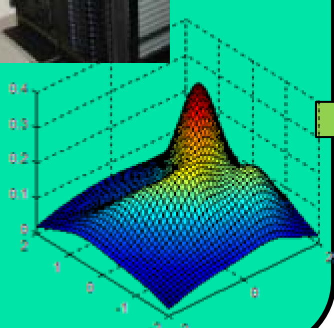
Technology adoption barrier

Risk Management

There is a significant adoption barrier that prevents risk managers to benefit from the develop (advanced) tools

Automated Risk Assessment

High fidelity simulation + surrogate modeling + probabilistic tools



Technology adoption barrier

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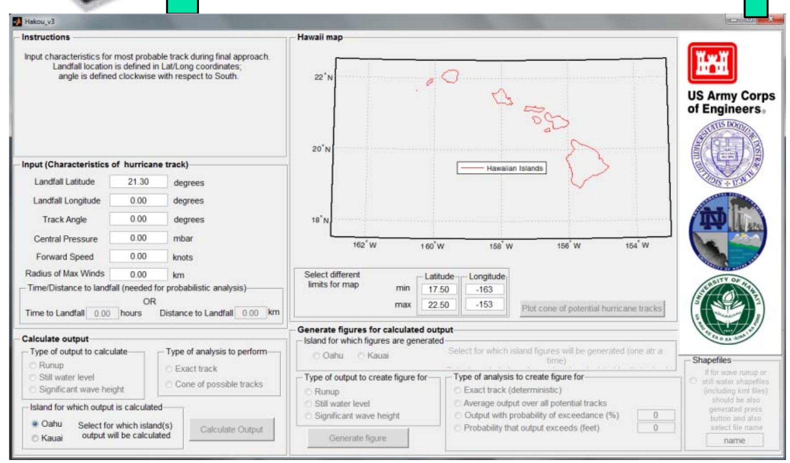
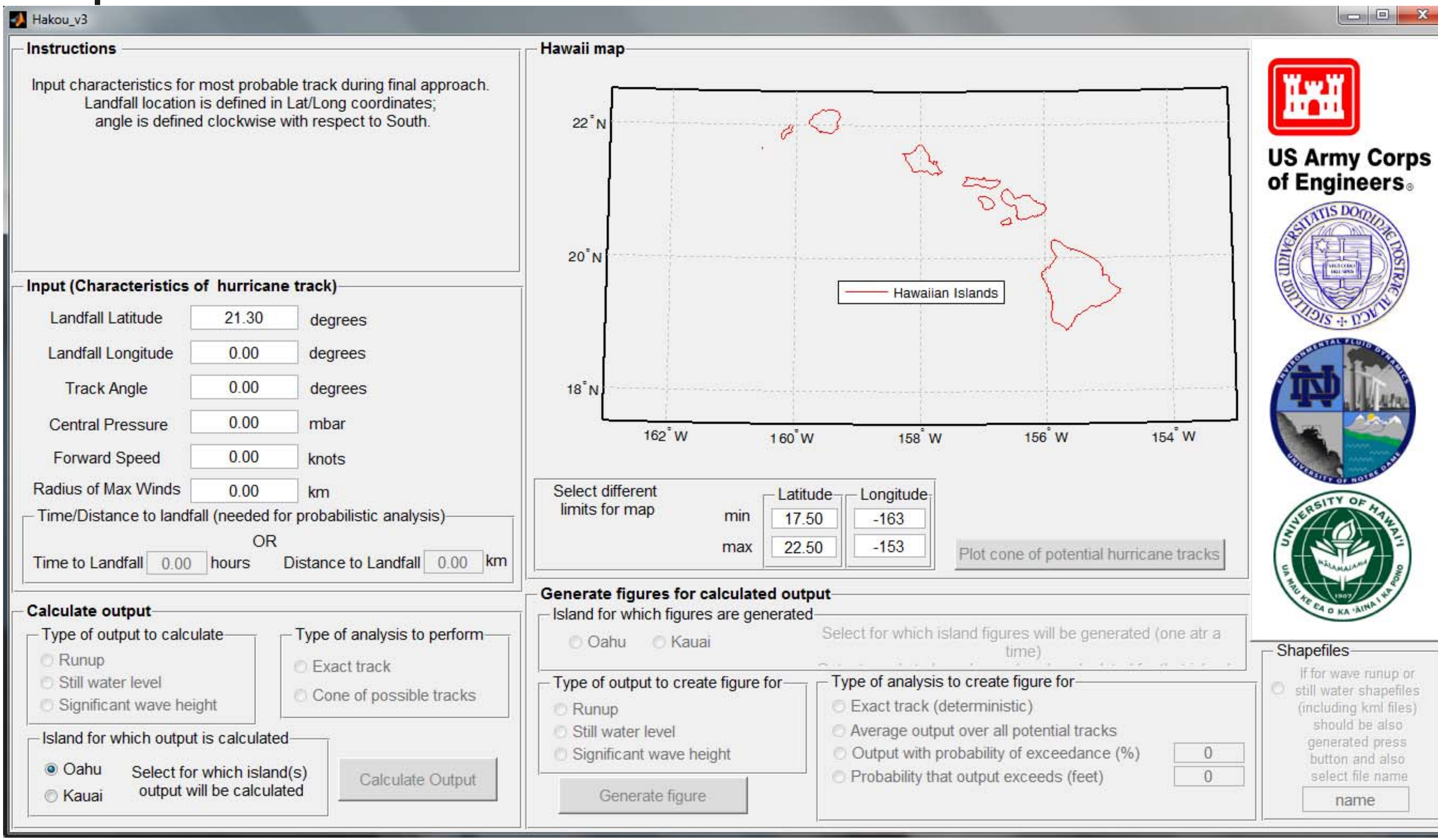


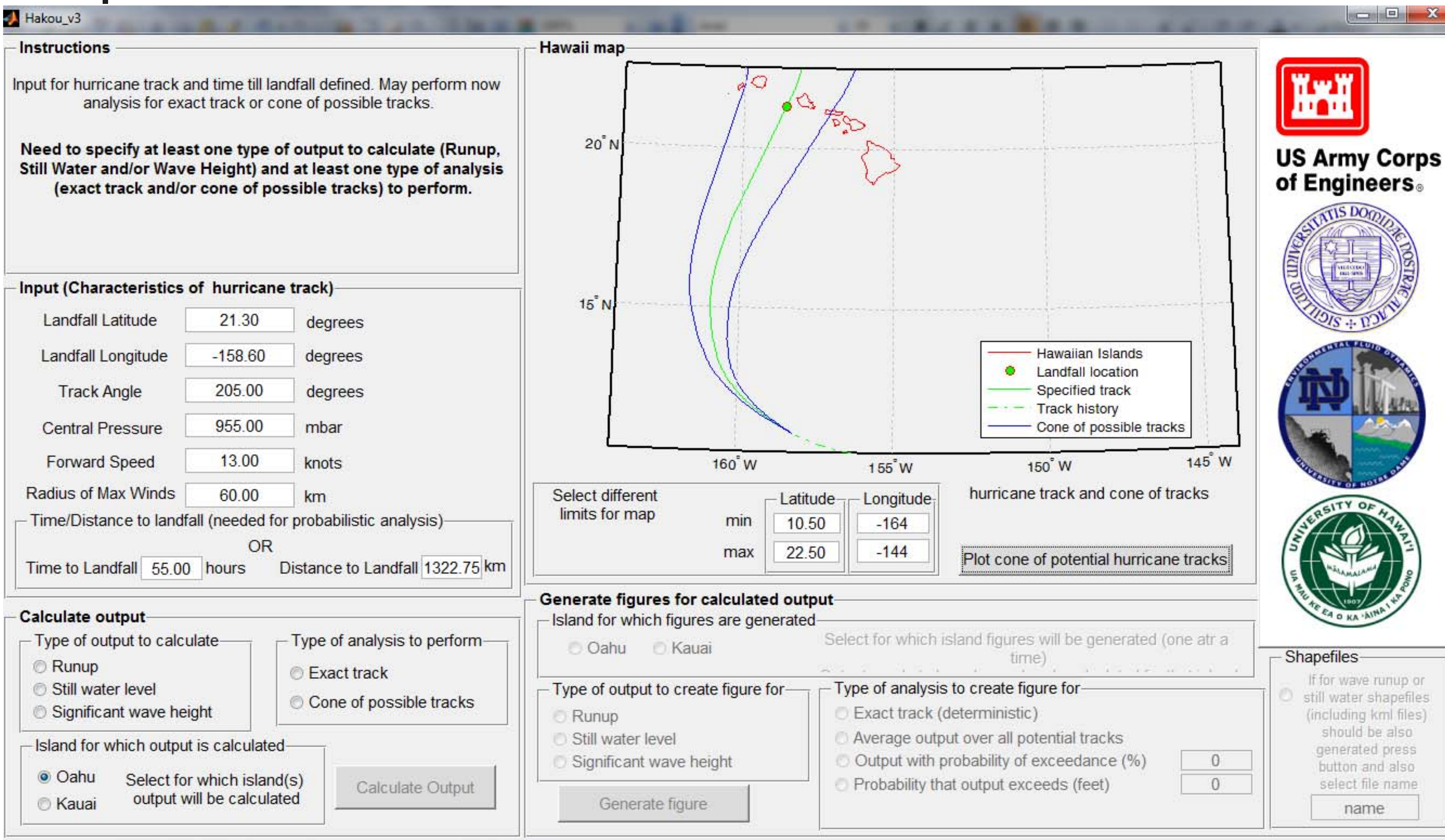
Risk Assessment tool

Exploit efficiency of surrogate model

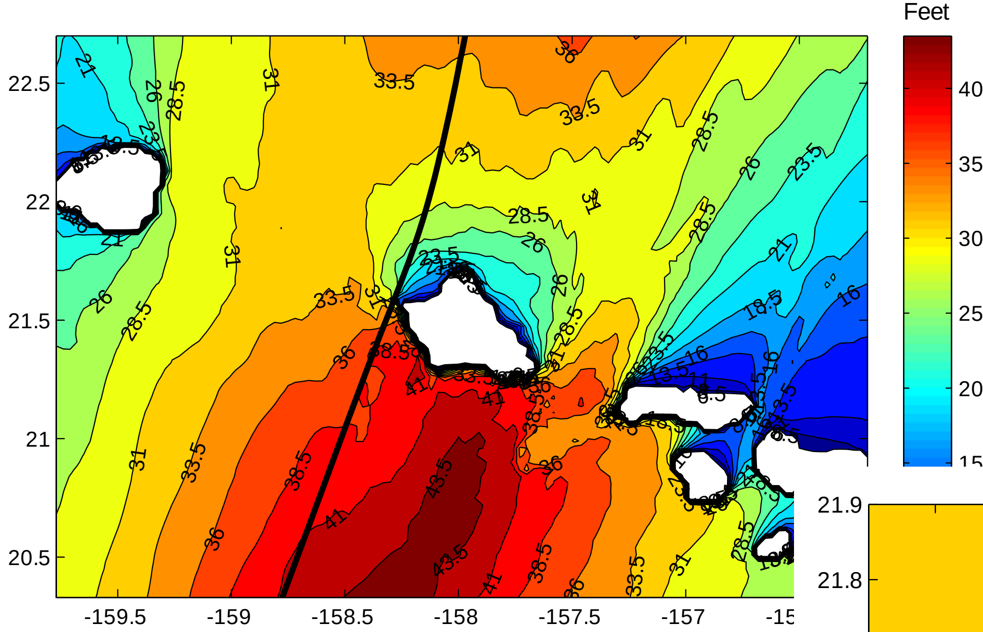
HAKOU Prediction Tool



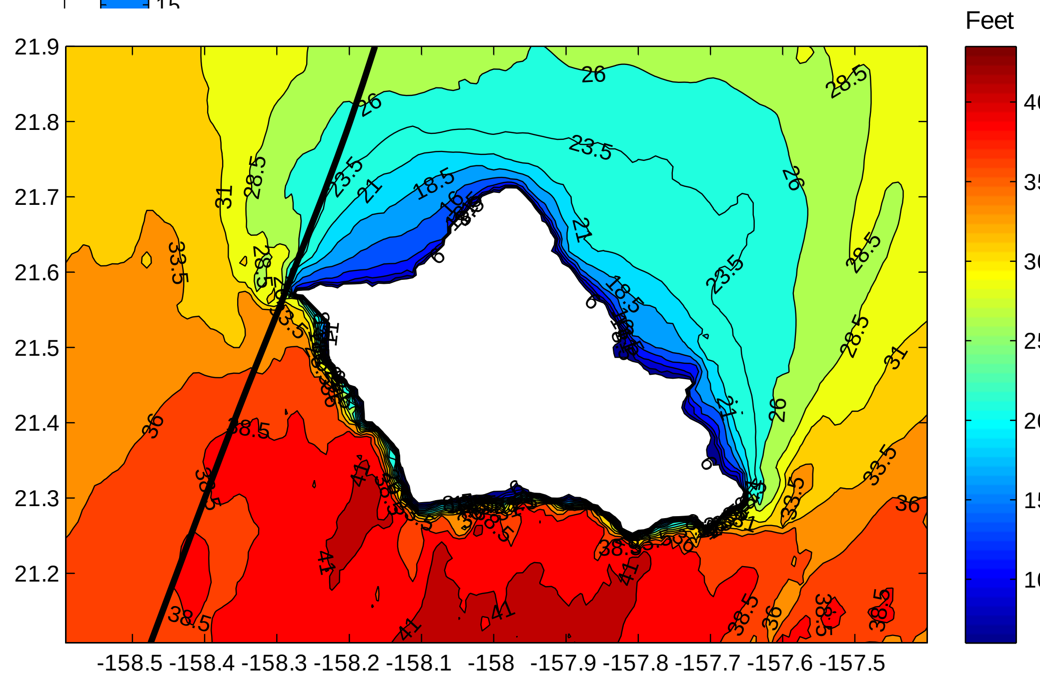
HAKOU Prediction Tool



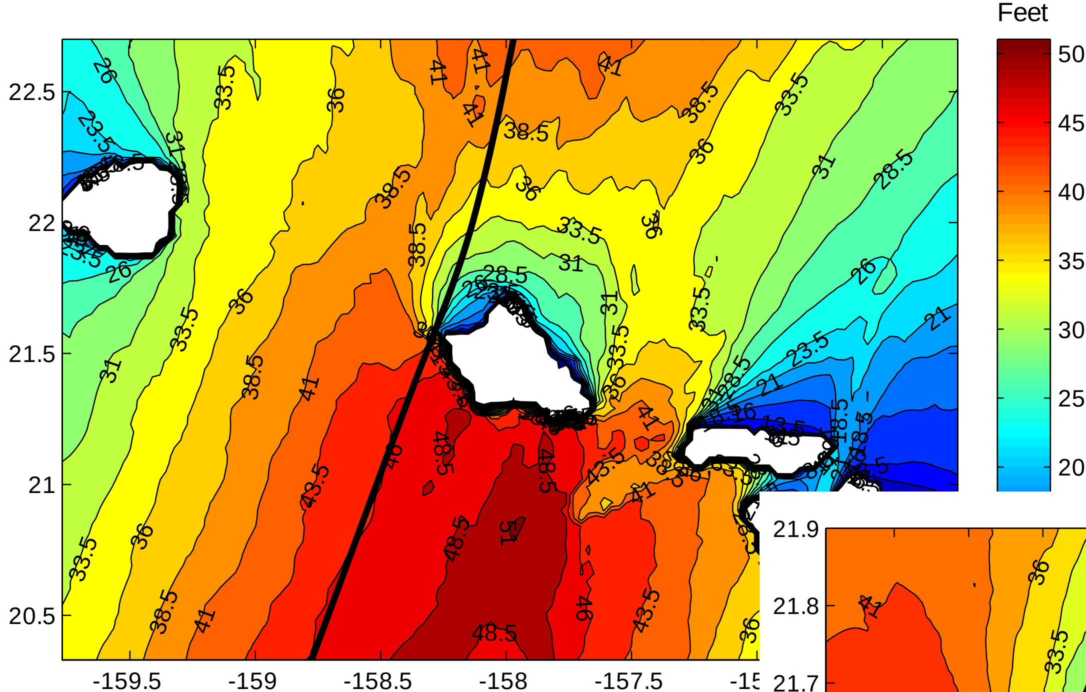
Significant Wave Height Output



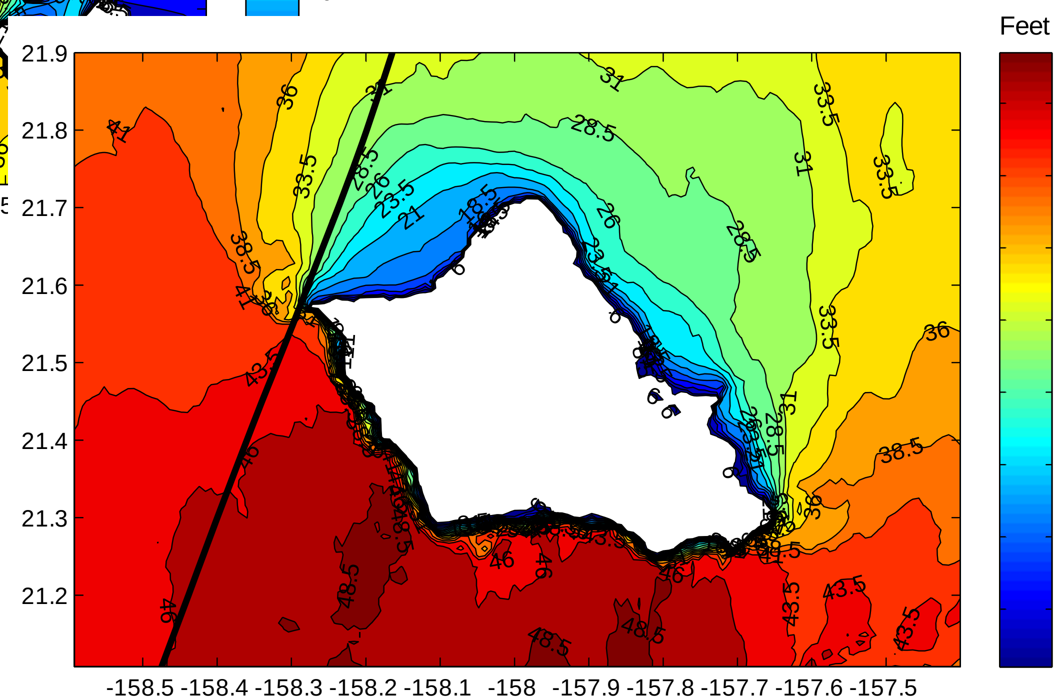
Expected significant wave height



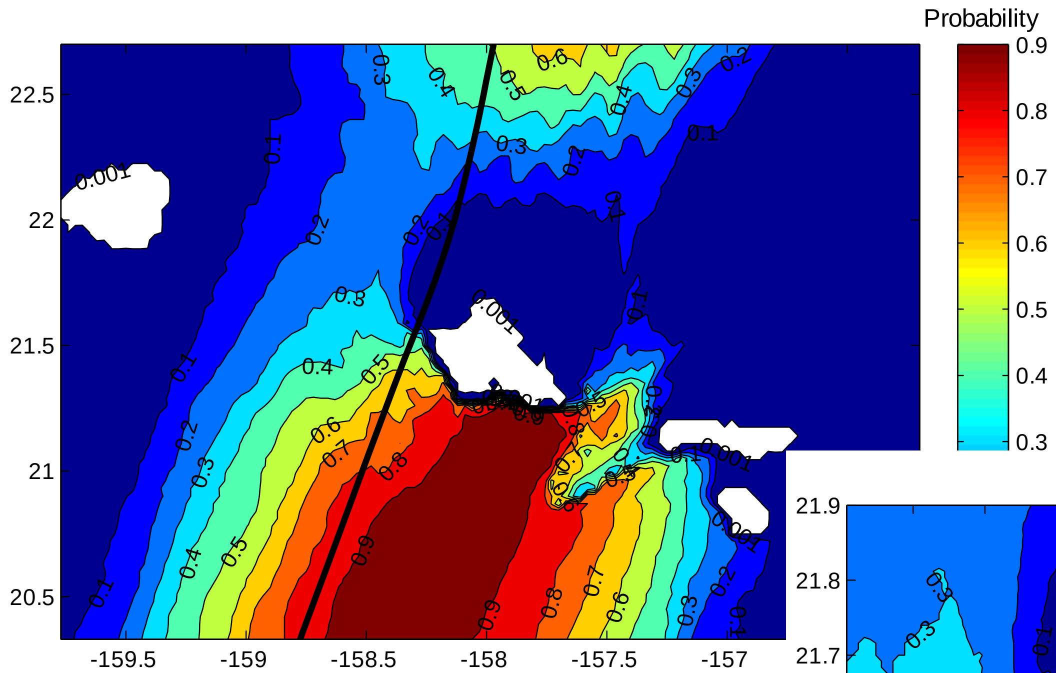
Significant Wave Height Output



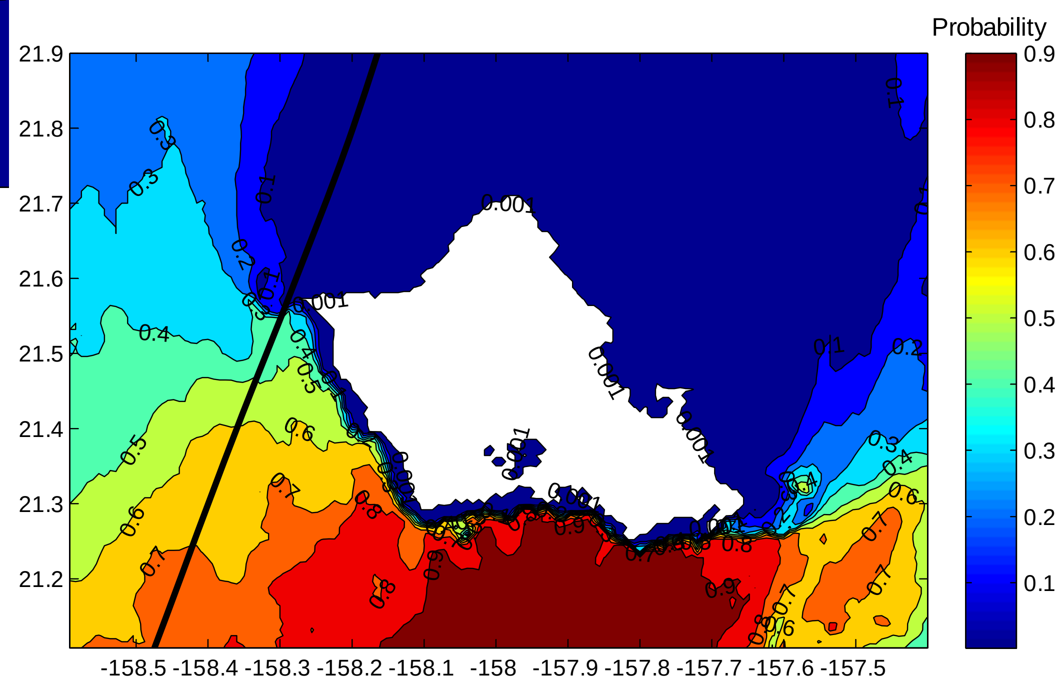
Significant wave height with probability of exceedance 10%



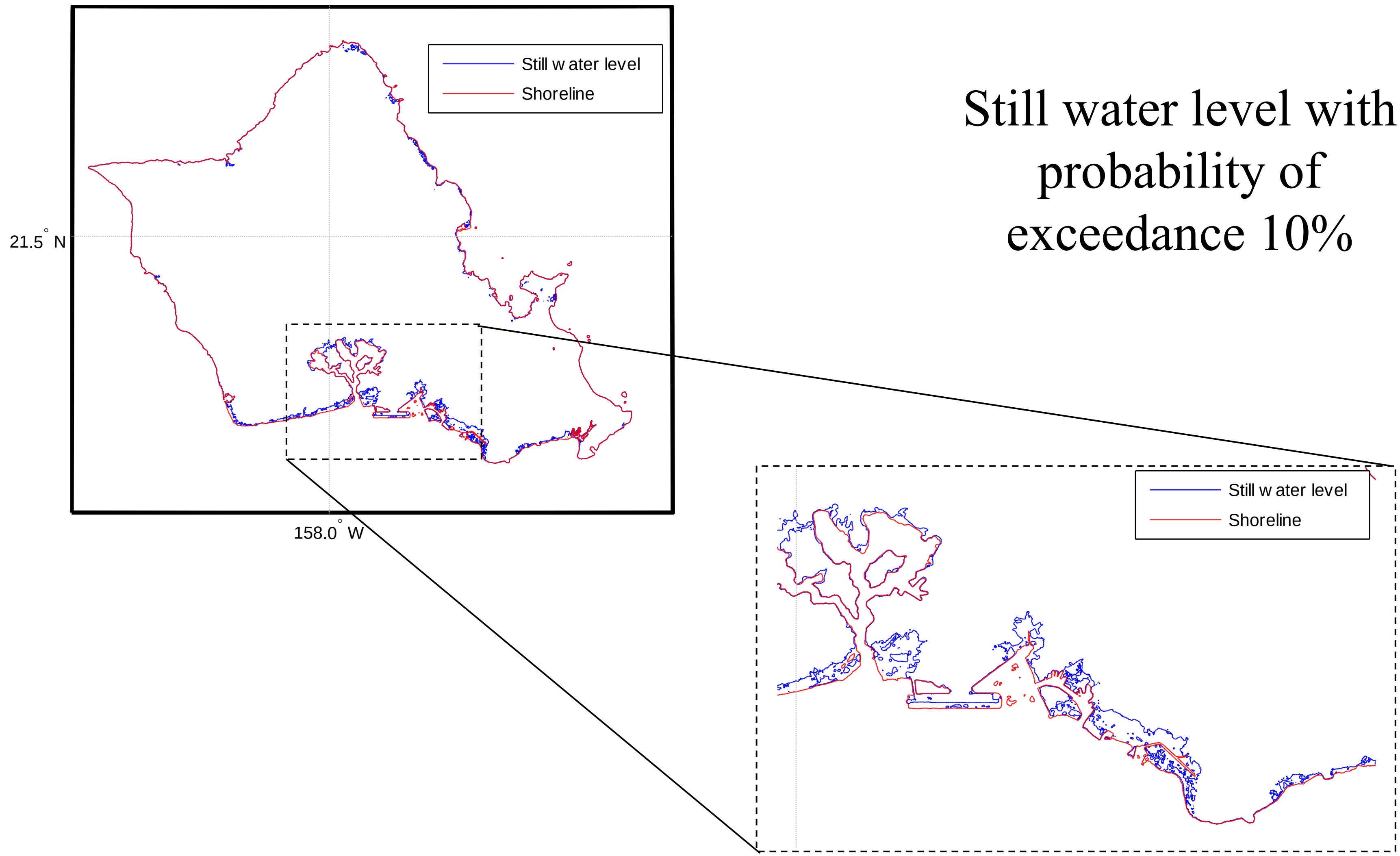
Significant Wave Height Output



Probability wave height with exceed 35feet

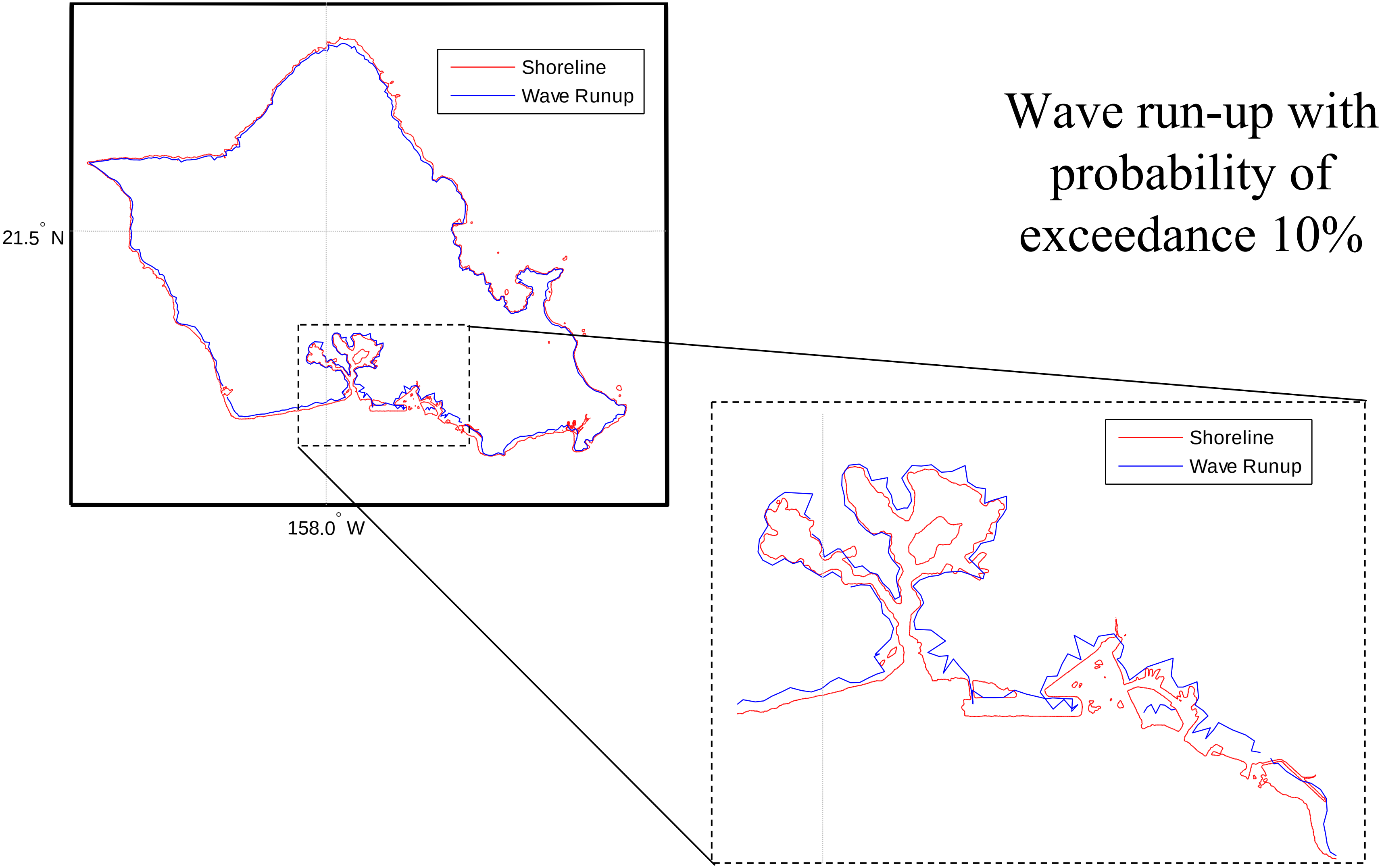


Still Water Level Output



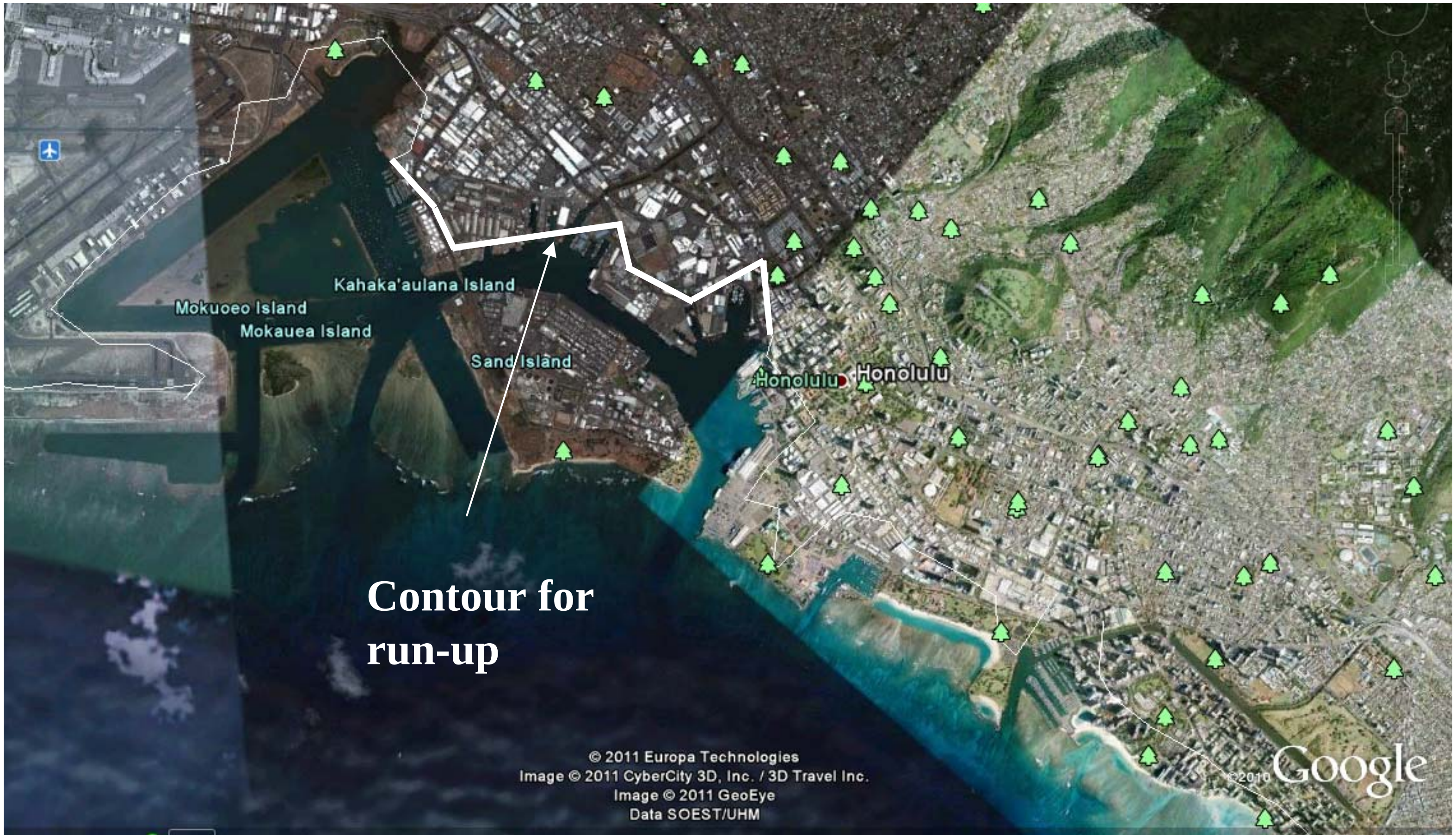
Still water level with probability of exceedance 10%

Wave Run-up Output



Wave run-up with probability of exceedance 10%

Incorporation on Google Earth



Conclusions

- A probabilistic framework was developed for rapid hurricane risk estimation focusing on real time applications (during an approaching hurricane)

- Framework is based on a simplified parametric description of hurricane track. It combines high-fidelity model simulations (accuracy) along with response surface surrogate modeling (efficiency)

- It facilitates a highly efficient estimation of hurricane risk, through a stand-alone applet, and can provide critical information for emergency response managers