REAL-TIME ASSESSMENT OF WAVE AND SURGE RISK DUE TO LANDFALLING HURRICANES

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In this work, a probabilistic framework is presented for real-time assessment of wave and surge risk for hurricanes approaching landfall. This framework has two fundamental components. The first is the development of a surrogate model for the rapid evaluation of hurricane waves, water levels, and runup based on a small number of parameters describing each hurricane: hurricane landfall location and heading, central pressure, forward speed, and radius of maximum winds. This surrogate model is developed using a response surface methodology fed by information from hundreds of pre-computed, high-fidelity model runs. For a specific set of hurricane parameters (i.e., a specific landfalling hurricane), the surrogate model is able to evaluate the maximum wave height, water level, and runup during the storm at a cost that is more than seven orders of magnitude less than the high fidelity models and thus meet time constraints imposed by emergency managers and decision makers. The second component to this framework is a description of the uncertainty in the parameters used to characterize the hurricane, through appropriate probability models, which then leads to quantification of hurricane-risk in terms of a probabilistic integral. This integral is then efficiently computed using the already established surrogate model by analyzing thousands of different scenarios (based on the aforementioned probabilistic description). Finally, by leveraging the computational simplicity and efficiency of the surrogate model, a simple stand-alone PC-based risk assessment tool is developed that allows non-expert end users to take advantage of the full potential of the framework. An illustrative example is presented that considers applications of these tools for hurricane risk estimation for Oahu. The development of cyber-infrastructure at the University of Notre Dame to further support these initiatives is also discussed.

Keywords: hurricane risk; response surface approximations; joint probability method; coastal hazard; cyber-infrastructure

INTRODUCTION

Hurricane risk assessment has received increased attention in the past decade, partly in response to the destructive 2004, 2005 and 2008 hurricane seasons (Dietrich et al. 2010; Kennedy et al. 2011). Conventional approaches to this assessment are based on parametric or non-parametric analysis of data from historical storms (Borgman et al. 1992) or on simulation of hurricane design events. A different methodology (Myers 1975), frequently referenced as the Joint Probability (JPM) Method, relies on a simplified description of hurricane scenarios through a small number of model parameters (Niedoroda et al. 2008; Resio et al. 2009). Description of the uncertainty in these parameters, through appropriate probability models, leads to a probabilistic characterization of the hurricane risk. This risk is ultimately expressed as a probabilistic integral over the uncertain parameter space, and its estimation requires numerical evaluation of the hurricane inundation for a large number of scenarios resulting from the adopted probabilistic description of the model parameters (Resio et al. 2009; Taflanidis et al. 2012).

One of the important recent advances in this field has been the development of high-fidelity numerical simulation models for reliable and accurate prediction of surge responses for a specific hurricane event (Resio and Westerink 2008). These models permit a detailed representation of the hydrodynamic processes, albeit at the cost of greatly increased computational effort. This increases significantly the computational cost for estimating hurricane risk, which requires evaluation of the response for a large number of hurricane scenarios. To alleviate this problem, a low-cost dimensional surge response function was proposed Irish, et al., (2009), but only addressed the variation with respect to hurricane storm size, intensity, and track, was restricted to hurricane surge only and limited to specific locations of interest on the Texas coast. Udoh and Irish (2011) presented preliminary discussions for extending these surge response functions to address additional hurricane model parameters, the forward speed and heading, whereas Song, et al., (2012) recently investigated the influence of regional changes in bathymetry on the surge response functions. Das, et al., (2010) developed a methodology for selecting the most appropriate storm within some given database.

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Extending these efforts, this paper offers a versatile theoretical and computational framework for evaluation of hurricane wave and surge risk with particular emphasis on real-time, automated estimation during landfalling hurricanes, and implementation for the Hawaiian Island of Oahu. The significant advancements offered are that (i) risk for a given hurricane scenario may be calculated rapidly for hundreds of thousands of locations in a coastal region of interest, and for any modeled quantity representing hurricane impact (e.g. surge, wave height, runup), (ii) all parameters used to describe the hurricane characteristics may be varied over their appropriate ranges, and (iii) the framework may be used to develop automated risk assessment tools that can be ultimately used by end-users without high technical expertise, thus crossing over barriers for adoption of the advocated technologies. This versatile framework has few constraints in its applicability. Its foundation is the development of a computationally-efficient surrogate model for approximation of the impact for any hurricane scenario. Simply put, the input hurricane parameters are the variables that drive a smart interpolation (based on pre-computed high-fidelity numerical simulations) of a hurricane response surface. A moving least squares response surface approximation is adopted for the surrogate model. This selection provides the intended versatility of the framework, as it does not rely on any assumptions for the variability of the hurricane wave/surge response with respect to the hurricane model parameters and is efficiently implemented for any quantity representing the hurricane impact. The proposed methodology ultimately facilitates rapid real time risk assessment, but it establishes this at a considerable upfront computational cost, namely to perform high-fidelity simulations to create the surrogate model. This model can be then coupled with forecasts from the National Hurricane Center to facilitate real-time risk estimation. During a landfalling hurricane, the National Hurricane Center forecasts the most probable hurricane track and also provides standard climatological errors for track, strength, etc., associated with this prediction. This forecast can be used to define a probabilistic integral quantifying hurricane risk which can be estimated real-time at a small computational cost using the surrogate model. Leveraging this computationally efficient framework, we also establish an assessment tool that allows non-expert end users to take advantage of the full potential of this methodology to evaluate risks. Figure 1 presents an overview of the proposed framework.

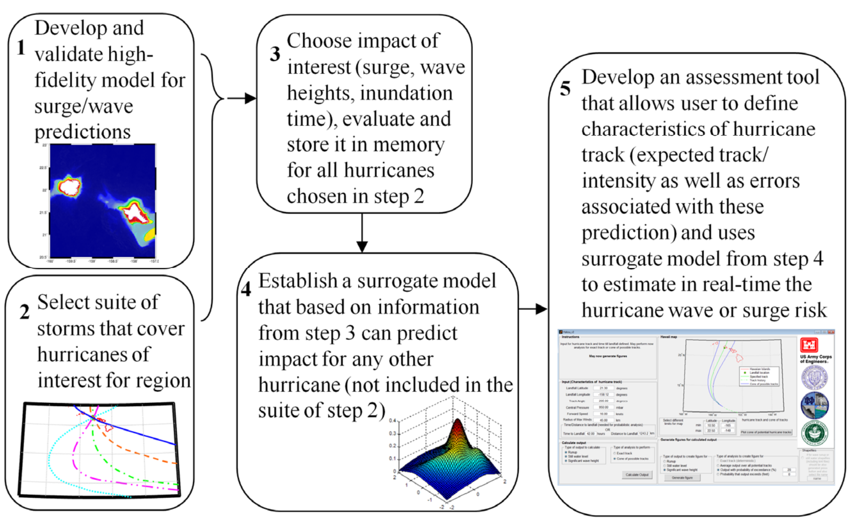

Figure 1: Schematic for development of framework for real-time hurricane risk assessment

PROBABILISTIC FRAMEWORK

Hurricane modeling

Each hurricane/storm event is approximated by a small number of model parameters, corresponding to its characteristics at landfall such as (i) landfall location x_o, (ii) track heading θ, (iii) central pressure c_p, (iv) forward speed v_f, (v) radius of maximum winds R_m, and (vi) tide level e_t. Typically a constant tide level is assumed (Resio et al. 2009) leading to the following definition of the model parameter vector, $\mathbf{x}$, describing each hurricane scenario

$$\mathbf{x} = [x_o \quad \theta \quad c_p \quad v_f \quad R_m]^T \qquad (1)$$

where $[]^T$ denotes a matrix transpose. Note that the discussions in this paper can be directly extended to include the tide level (or any other appropriate hurricane characteristic) as a model parameter. The implicit assumption is, though, that **x** is low dimensional (includes less than 8-10 parameters). This is necessary for facilitating an efficient description through a surrogate model, without requiring an overly large database to adequately describe the variability with respect to all the model parameters. The variability of the hurricane track and characteristics prior to landfall is also important. Directly incorporating, though, this variability in the hurricane description would increase significantly the number of model parameters and so it is avoided here. Instead this variability is approximately addressed by appropriate selection of the hurricane track history prior to landfall, so that important anticipated variations, based on historical data, are efficiently described (Resio et al. 2009).

To represent hurricane impact in the coastal region of interest, and ultimately to quantify risk, several response quantities may be examined simultaneously in this framework. Examples of such quantities are (i) the still water level (SWL), i.e. storm surge ζ, defined as the average sea level over a several minute period, (ii) the wave runup level (WRL), defined as the sea level including runup of wind waves on the shore, (iii) the significant wave height (H_s) (possibly along with the corresponding peak period T_p), or (iv) the time that normally dry locations are inundated. In this study we will focus on the first three. Once the response parameters of interest have been determined, we let **z** denote the vector of response quantities (i.e., **z** is the response as a function of the spatial variables x and y). This vector will be referenced herein as the response vector and will be used to quantify hurricane risk. Each component of **z** pertains to a specific response variable [any of the (i)-(iv) described above] for a specific location. The augmentation of all these responses for all different locations in our region ultimately provides the n_z-dimensional vector **z**. The dimension of n_z can be, thus, very large.

This response vector **z** for a specific hurricane scenario, described by the model parameter vector **x**, may be accurately estimated by numerical simulation, once an appropriate high-fidelity model is established (see discussion later). Since the high-fidelity model requires extensive computational effort for each analysis, a surrogate model is also developed for simplification of the risk evaluation (see discussion later). This surrogate model is based on information provided by a number of pre-computed evaluations of the computationally intensive high-fidelity model, and ultimately establishes an efficient approximation to the entire response vector for each hurricane scenario. The relationship between each component of the actual response z_i and corresponding component of the response that is provided through the surrogate model $\hat{z}_i$ is ultimately expressed as

$$z_i(\mathbf{x}) = \hat{z}_i(\mathbf{x}) + \varepsilon_i \qquad (2)$$

where ε_i is the prediction error between the surrogate model and the high-fidelity model, assumed to be zero mean (since the contrary indicates a bias) Gaussian random variable with standard deviation σ_{ε_i}. This choice of probability distribution incorporates the largest amount of uncertainty (Taflanidis and Beck 2010), in terms of Information Entropy, under the constraints that only the mean and variance are known. The standard deviation σ_{ε_i} can be finally approximated by comparison of the high-fidelity and surrogate models over a set of hurricane scenarios chosen to serve as validation points. This then completely defines the prediction error ε_i and the relationship between $z_i(\mathbf{x})$ and $\hat{z}_i(\mathbf{x})$ in a probabilistic sense. Note that additional modeling errors can be incorporated in the relationship (2) , for example the errors introduced by the approximate description of hurricane by a small dimensional vector **x** (Resio et al. 2009; Taflanidis et al. 2012) or the errors associated with the assumptions made about tides. These errors can be similarly probabilistically characterized, though determining their statistics is not as straightforward because a set of scenarios for validation is not typically available.

Hurricane risk quantification

Hurricane risk may be then quantified in terms of the response $\hat{\mathbf{z}}$ provided by the surrogate model and the *probability density function* $p(\mathbf{x})$ describing the uncertainty in the input hurricane parameters. For real-time risk evaluation, i.e., predicting the risk due to an approaching hurricane, $p(\mathbf{x})$ may be constructed through standard climatological error estimates provided by the National Hurricane Center (http://www.nhc.noaa.gov/verification/verify4.shtml). This information can be then used to adopt a probabilistic description for the model parameters. In this case, each component of **x** can be selected to follow an independent Gaussian distribution with mean equal to the forecast quantities and standard deviation equal to the associated statistical error. On the other hand, for long-term hurricane risk evaluation for a region (Resio et al. 2009), $p(\mathbf{x})$ is selected based on statistical data or atmospheric models for the entire region (Emanuel et al. 2006) and it further incorporates information on occurrence rates for hurricanes, not just on relative plausibility of the model parameters. The study by Resio et al. (2009) includes a detailed discussion for selection of $p(\mathbf{x})$ for the Gulf of Mexico.

Risk is finally expressed as some desired statistic of the response $\mathbf{z}$, for example the probability that the wave height will exceed some specific threshold or the median wave runup. The exact selection used for these statistics leads to definition of the risk consequence measure $h(.)$. Ultimately for any component z_i of the response vector the risk, denoted R_j, is provided by the probabilistic integral

$$R_i = \int_X h[\hat{z}_i(\mathbf{x})]p(\mathbf{x})d\mathbf{x} \tag{3}$$

where X corresponds to the region of possible values for $\mathbf{x}$. Through appropriate selection of $h(.)$ all potential hurricane risk quantifications can be addressed through this approach. For example, if R_j corresponds to the expected value for some z_i then $h[.] = \hat{z}_i(\mathbf{x})$. If on the other hand R_j corresponds to the probability that some z_j will exceed some threshold β_i then (Taflanidis and Beck 2008) $h[.] = P_i(\hat{z}_i - \beta_i)$ where $P_i(.)$ corresponds to the cumulative distribution function for the model prediction error ε_i. This simplifies to

$$h[\hat{z}_i(\mathbf{x})] = \Phi\left[\frac{\hat{z}_i(\mathbf{x}) - \beta_i}{\sigma_{e_i}}\right] \tag{4}$$

for the proposed case of Gaussian distribution for the model prediction error, where $\Phi[.]$ denotes the standard Gaussian cumulative distribution function. Note that this measure explicitly includes model error estimates, as model predictions less than the threshold β_i may still have a small probability of exceeding the threshold and vice versa. As the model prediction error approaches zero, the risk measure collapses to zero if $\hat{z}_i(\mathbf{x}) < \beta_i$, and one if $\hat{z}_i(\mathbf{x}) > \beta_i$.

Hurricane risk estimation

The risk integral in Equation (3) can be estimated by stochastic simulation (Robert and Casella 2004). For the simplest approach (Direct Monte Carlo), and using N samples of $\mathbf{x}$ randomly selected from $p(\mathbf{x})$, the estimate for R_i is given by

$$\hat{R}_i = \frac{1}{N}\sum_{k=1}^{N} h[\hat{z}_i(\mathbf{x}^k)] \tag{5}$$

where vector $\mathbf{x}^k$ denotes the sample of the uncertain parameters used in the k^{th} simulation. As $N \to \infty$, then $\hat{R}_i \to R_i$ but even for finite, large-enough N, Equation (5) gives a good approximation for the risk given by Equation (3). The quality of this approximation is assessed through its coefficient of variation, δ obtained by (Robert and Casella 2004)

$$\delta \approx \frac{1}{\sqrt{N}}\sqrt{\frac{\frac{1}{N}\sum_{k=1}^{N}\left(h[\hat{z}_i(\mathbf{x}^k)]\right)^2}{\hat{R}_i^{\,2}} - 1} \tag{6}$$

which decreases [improved accuracy for estimation of (3)] proportional to $\sqrt{N}$. Exploiting the computational efficiency of the surrogate model (used for estimation of $\hat{z}_i$) a large value can be selected for N, facilitating thus a high-accuracy estimate. This accuracy may be further improved by adopting some advanced stochastic simulation approaches for variance reduction, such as Importance Sampling (Taflanidis and Beck 2008).

Note that this stochastic-simulation-based risk assessment approach facilitates an efficient estimation of risk for different quantifications (different selections for $h[.]$) since the response $\{\hat{z}_i(\mathbf{x}^k);\ k = 1,\ldots,N\}$ needs to be estimated only once; the various selected risk quantifications then require merely estimation of the different risk consequence measures $h[.]$ which is computationally straighforward.

HIGH-FIDELITY HURRICANE RESPONSE EVALUATION

For any given hurricane scenario, the parameter vector **x** along with the chosen hurricane track history defines the wind and pressure fields over time through a parametric hurricane model (Phadke et al. 2003). Using these wind and pressure fields, the surge and wave response for the entire coastal region of interest can be calculated with a high-fidelity model, which for this study is SWAN+ADCIRC (Westerink et al. 2008). ADCIRC solves the shallow-water equations for water levels and the momentum equations for currents. The variables are defined on unstructured triangular finite element grids at the vertices (Westerink et al. 2008). Waves are computed using the unstructured version of the SWAN non-phase resolving wind wave model. SWAN solves for wave action density which evolves in time, geographic space and spectral space. Source terms in the governing wave action density equation account for wave growth by wind; action lost due to whitecapping, surf breaking and bottom friction; and action exchanged between spectral components due to nonlinear effects in deep and shallow water. The unstructured grid version of SWAN is based on triangular elements with the action density function being defined at the vertices. Of course, waves and circulation interact despite being well separated in frequency space. SWAN+ADCIRC have been fully integrated into a comprehensive modeling system allowing full interaction between model components. Since the variables for both models are defined at identical locations (i.e. triangle based vertices), there is no interpolation that has to be performed between the two models. Furthermore in the highly efficient parallel implementation of SWAN+ADCIRC, all inter-model communication is intra-core, and while intra-model communications in inter-core, it is predominantly local along the sub-domain edges and only between adjacent sub-domains. This makes the combined code highly scalable and efficient.

Additionally, wave action can increase inundation considerably in the swash zone at the ocean's edge, which is intermittently wet and dry, from wave runup and drawdown. An approximate approach is adopted here for efficient evaluation of these effects; a large number of one dimensional transects are defined along the perimeter of the region of interest, with each transect extending 1000m inland and up to 2000m offshore. A two dimensional array of initial water levels and wave heights is then defined at the offshore end of each transect, with values based on information about the anticipated wave environment characteristics provided through the initial SWAN+ADCIRC runs. One dimensional Boussinesq model analysis is then performed for all these parameter combinations, yielding a prediction for the wave runup along each transect (Demirbilek et al. 2009). These results are then used through a simple interpolation scheme, to provide an estimate of maximum inundation distance along that transect for any input for wave or water level.

RESPONSE SURFASE SURROGATE MODELING

Moving least squares response surface approximation for a scalar output

A response-surface (Myers and Montgomery 2002) surrogate model approach is adopted here to approximate in real-time the response **z** obtained by the computationally expensive ADCIRC+SWAN numerical model. This is established by expressing each $z_i(\mathbf{x})$, where **x** is the n_x=5-dimensional vector defining the hurricane characteristics, through j=1,…,NB preselected basis functions $b_j(\mathbf{x})$ through introduction of coefficients $a_{ij}\{\mathbf{x}\}$

$$\hat{z}_i(\mathbf{x}) = \sum_{j=1}^{NB} b_j(\mathbf{x}) a_{ij}\{\mathbf{x}\} = \mathbf{b}(\mathbf{x})^T \mathbf{a}_i\{\mathbf{x}\} \tag{7}$$

where $\mathbf{b}(\mathbf{x})$ and $\mathbf{a}_i\{\mathbf{x}\}$ are the vectors containing the basis functions and coefficients, respectively. A common choice for basis functions is a complete second order approximation:

$$z_i(\mathbf{x}) = a_{i0}\{\mathbf{x}\} + \sum_{j=1}^{n_x} a_{ij}\{\mathbf{x}\} x_j + \sum_{j=1}^{n_x}\sum_{k\geq j}^{n_x} a_{ijk}\{\mathbf{x}\} x_j x_k\,;\quad NB = \frac{n_x(n_x+3)+2}{2} \tag{8}$$

leading to

$$\begin{aligned} &\mathbf{b}(\mathbf{x}) = \begin{bmatrix} 1 & x_1 & \dots & x_{n_x} & x_1^2 & x_1x_2 & \dots & x_{n_x}^2 \end{bmatrix} \\ &\mathbf{a}_i\{\mathbf{x}\} = \begin{bmatrix} a_{i0}\{\mathbf{x}\} & a_{i1}\{\mathbf{x}\} & \dots & a_{in_x}\{\mathbf{x}\} & a_{i11}\{\mathbf{x}\} & a_{i12}\{\mathbf{x}\} & \dots & a_{in_xn_x}\{\mathbf{x}\} \end{bmatrix} \end{aligned} \tag{9}$$

The coefficients $\mathbf{a}_i\{\mathbf{x}\}$ are calculated by initially evaluating $z(\mathbf{x})$ (through the high-fidelity numerical model) for a set of hurricane scenarios with characteristics spanning the entire region of interest for $\mathbf{x}$ (representing probable and significant future hurricane scenarios), and then by minimizing a weighted mean squared error over these scenarios between $z_i(\mathbf{x})$ and the approximation established through Equation (7) (Choi et al. 2001; Myers and Montgomery 2002). The weights in this mean squared error are also a function of $\mathbf{x}$ (what is formally known as moving least squares response surface approximation); this improves the efficiency of the approximation by giving higher importance to high-fidelity hurricane scenarios (support points) that are similar to the new scenario which we are trying to approximate (Taflanidis 2012). Appendix B provides further details on these tasks. Ultimately the approximation established through the moving least squares response surface is given by

$$\hat{z}_i(\mathbf{x}) = \mathbf{b}^T(\mathbf{x})\mathbf{M}^{-1}\{\mathbf{x}\}\mathbf{L}\{\mathbf{x}\}\mathbf{F}_i \tag{10}$$

where matrices $\mathbf{M}\{\mathbf{x}\}$, $\mathbf{L}\{\mathbf{x}\}$ and $\mathbf{F}_i$ are defined in Appendix A, and depend on the weighting functions selected for the interpolation as well as vectors $\mathbf{b}(.)$ and $\mathbf{z}(.)$ evaluated at the locations of the support points.

Implementation for surge prediction for inland locations

Though the response surface approximation described in the previous section is a generalized one, i.e., it does not depend on the characteristics of the response quantity z_i, its implementation for inland locations needs to additionally address the challenge that they do not *always* get inundated (in other words dry locations might remain dry for some storms). Though some scenarios in the database include full information for the surge height ζ_i (when location i gets inundated), some provide *only* the information that the location remained dry. One solution to this problem is to develop a surrogate model (Burges 1998) for the binary response quantity describing the condition of the location, i.e., either wet or dry. If we additionally need to know the storm surge ζ_i, some alternative approach needs to be established, one that allows each scenario in our database to provide full, exact or approximate, information for ζ_i. To facilitate this, the following approach is proposed. The surge height ζ_i is described with respect to the zero sea level as reference point. When a location remains dry the surge height for it is selected as the one corresponding to the nearest location (nearest node in our high-fidelity numerical model) that was inundated. Figure 2 illustrates this approximation for an example with a one-dimensional transect (note that this approach is ultimately applied in the context of the full high-fidelity model, not simply with respect to one-dimensional transects). Once the database is adjusted for ζ_i (for the scenarios for which the location remained dry), the response surface approximation for ζ_i follows directly the steps discussed in the previous section. Comparison of ζ_i to the elevation of the location provides finally the answer as to whether the location was inundated or not, whereas the storm surge is calculated by subtracting these two quantities. Thus this approach allows us to gather simultaneous information about both the inundation (binary answer; yes or no) as well as the storm surge elevation. More importantly, it falls within the generalized response surface model discussed in the previous section. Of course it does involve the approximation illustrated in Figure 2 for enhancing the database with complete information for ζ_i for all hurricane scenarios.

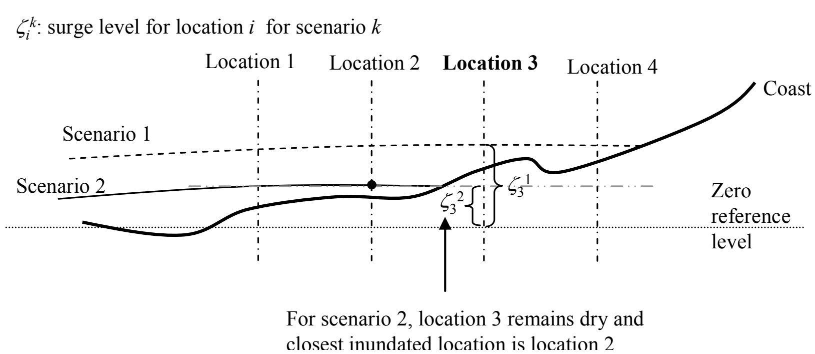

Figure 2. Illustration of selection of surge height for an example with a one-dimensional transect. Corrections for the surge in location 3 are shown

Response surface approximations for entire response vector z

The approximation for the entire vector **z** is established by approximating each z_i through Equation (10) and augmenting in vector format the results. This is ultimately expressed in a simple mathematical form as

$$\hat{\mathbf{z}} = \mathbf{b}^T(\mathbf{x})\mathbf{M}^{-1}\{\mathbf{x}\}\mathbf{L}\{\mathbf{x}\}\mathbf{F} \quad \text{where} \quad \mathbf{F} = [\mathbf{F}_1 \quad \mathbf{F}_2 \quad \ldots \quad \mathbf{F}_{n_z}] \qquad (11)$$

This is a computationally-inexpensive approximate model (only based on matrix manipulations); thus it can be exploited for real-time predictions, but requires that a large number of high-fidelity model simulations be performed in advance (this information is ultimately included in **F**). Note that information from models runs (SWAN+ADCIRC) is only incorporated in **F**; the rest of the matrices in (11) are independent of any model. As such the approach is extendable to any output of interest and can be easily augmented to include information from additional high-fidelity simulations as they become available. Finally, the statistics of the prediction error due to the response surface surrogate modeling can be approximated by the statistics of the difference $\{z_i(\mathbf{x}_p)-\hat{z}_i(\mathbf{x}_p)\}$ over any sample set of hurricane scenarios described by $\{\mathbf{x}_p; p=1,\ldots,N_E\}$ chosen to act as validation points for the response surface. This leads to the following maximum likelihood estimate for the prediction error standard deviation (Grimmett and Stirzaker 2001)

$$\sigma_{\varepsilon_i} = \sqrt{\frac{1}{N_E}\sum_{p=1}^{N_E}\left(z_i(\mathbf{x}_p)-\hat{z}_i(\mathbf{x}_p)\right)^2} \qquad (12)$$

This completely defines the probability model for the prediction error ε_i since it has been already assumed to follow a zero mean Gaussian distribution.

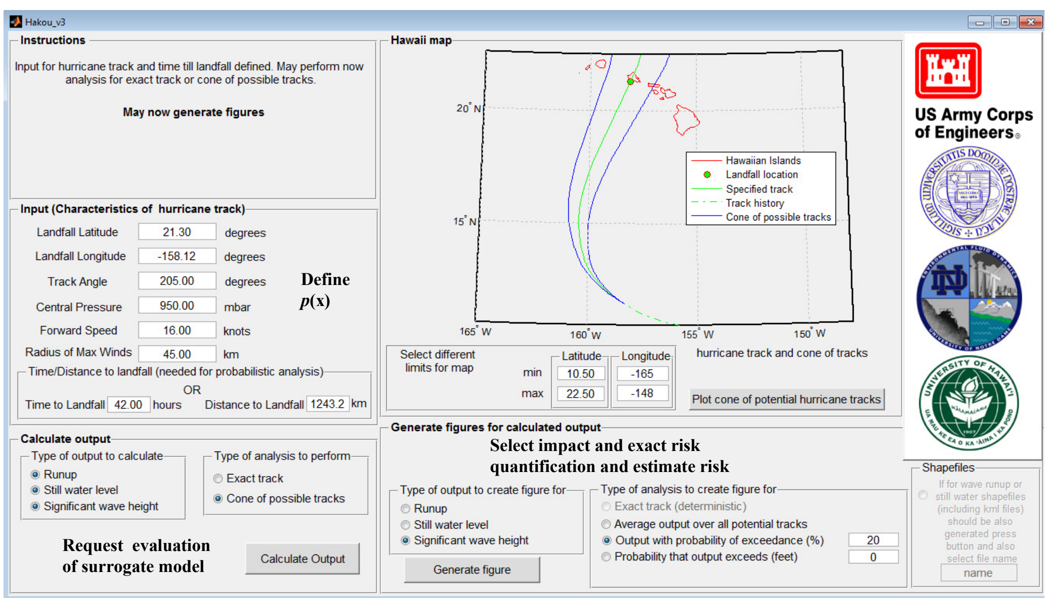

Figure 3: Graphical user interface for automated risk assessment tool

AUTOMATED RISK ASSESSMENT

The theoretical/computational developments in the proposed framework share one significant drawback: their complexity creates a technological barrier that effectively isolates them from non-expert users. As a result, these advances may not directly translate to the intended benefactors of the risk assessment framework (decision makers) and the constituents they serve (public at large). To reduce this barrier between this methodology and end users, automated risk assessment tools can be developed by leveraging the computational simplicity and speed of the proposed surrogate model, which is only based on simple matrix manipulations. These resulting standalone tools require minimum computational resources to run as they perform only simple mathematical manipulations expressed through equations (2) and (7), as well as access to the database of high-fidelity model runs. Figure 3 shows the Graphical User Interface (GUI) of the tool developed for the illustrative example that will be considered next, which examines inundation risk over the coastline of Oahu for an approaching hurricane. Through this tool the user can define track and strength characteristics (and thus $p(\mathbf{x})$ as previously discussed) and then request evaluation of the response, which is rapidly computed based on the surrogate model. The user can then select some risk quantification for a specific response of interest (for example probabilistic mean surge or wave height when a storm is 48 hours from landfall), which defines $h(.)$ as discussed previously, and finally request calculation of the risk based on (2). Ultimately such tools allow non-technical end-users to leverage the full power of the proposed risk assessment framework and can be used for planning emergency response during real hurricane events approaching landfall, or for making long-term planning decisions based on fictitious scenarios.

APPLICATION TO REAL-TIME RISK ESTIMATION FOR OAHU

High fidelity model and simulations

The computational domain developed for the high-fidelity simulation of the hurricane response in this study, encompasses a large portion of the northern Pacific Ocean and extends from 0 (equator) to 35 degrees north and from 139 to 169 degrees west. The grid incorporates 1,590,637 nodes and 3,155,738 triangular elements. Minimum grid resolution at the domain edge is 10km, and maximum resolution of 30m is found in complex coastal areas such as bays and harbors. Bathymetric (Figure 3) and topographic data applied to the grid came from a variety of sources. For the numerical simulation, SWAN applies 10 minute time steps while ADCIRC applies 1 second time steps. A SWAN+ADCIRC simulation runs in 16 wall clock minutes per day of simulation on 1024 cores on Diamond, a 2.8 GHz dual quad core based machine with a 20 Gbit/sec InfiniBand interconnect (http://www.erdc.hpc.mil/). This model was validated by simulating tides as well as by hindcasting Hurricane Iniki (1992), comparing to water levels as well as wind wave data. More details on the model itself and the validation may be found in (Kennedy et al. 2012).

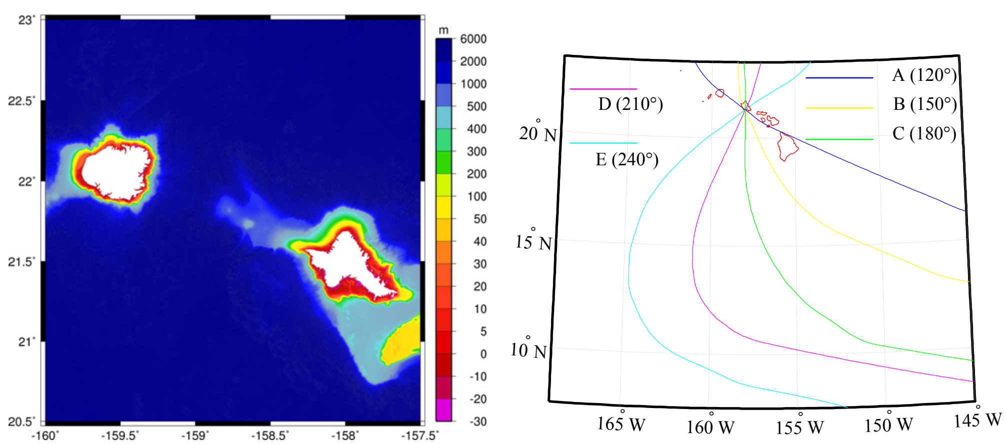

Figure 4: Bathymetry of the grid around Oahu and Kauai (left) and Basic storm tracks (right)

Based on information from the NWS on historical storms, a suite of hurricane scenarios was created. These scenarios will ultimately correspond to the support points for the surrogate model, and were chosen so that they cover most future hurricane events that are anticipated to have significant impact on Oahu. Five basic storm tracks were considered, representing different angles of final approach θ. These tracks are shown in Figure 4. Landfall was defined to correspond to the point where each hurricane crosses 21.3 degrees north and fourteen different landfall locations, x_o, were chosen for the grid of storms, corresponding to 157.60, 157.85, 158.10, 158.30, 158.60, 158.90, 159.20, 159.50, 159.80, 160.00, 160.40, 160.70, 161, 161.5 degrees West. Three different values for the central pressure c_p were used, 940, 955 and 970 mbar, and similarly three different cases for the forward velocity v_f were considered, 7.5, 15 and 22.5 knots. Finally two different values were considered for the radius of maximum winds, R_m, 30 and 60 km. A suite of 630 storms was then selected to efficiently describe the entire grid of hurricane scenarios generated through these potential parameter values. The response for these storms was then computed by the ADCIRC+SWAN model, a process which required ultimately more than 1,200,000 computational hours. Such simulations can be performed outside of hurricane season, removing real-time forecasting constraints on time to execute runs and perform quality control. All results of interest were stored, including maximum significant wave heights and surge levels throughout each simulation. All analyses were performed assuming high tides of 0.4m, taken to represent worst-case scenario for the hurricane risk in this region.

For the wave breakup 750 transects were considered around the island and for each transect a matrix of 169 combinations of wave height and water level was created. The maximum and minimum values of these parameters for each transect were selected based on the information from the 630 runs. For each case the inundation was then predicted by a 1-D Boussinesq analysis. If z_{wk} is the wave break up response at transect k and H_{sk} and ζ_{sk} are the corresponding wave height and still water level, respectively, then this approach leads to a mapping of the form $z_{wk}=g(H_{sk},\zeta_{kj}|D_D)$, where D_D represents the data obtained through the 169 1-D Boussinesq analyses for each transect.

Surrogate model

Using the information from the pre-computed 630 storms, a moving least squares response surface surrogate model was built. Full quadratic basis functions were chosen for x_o, θ, c_p, v_f and linear basis functions for R_m, and the common Gaussian weight function in Equation (5) is adopted with D_d adaptively selected so that it includes for each $\mathbf{x}$ 100 support points (out of the possible 630). To evaluate the fit of the surrogate model and further estimate the prediction error variance based on Equation (8) 20 hurricane scenarios were chosen to represent the validation set for the surrogate model. The characteristics for these scenarios were randomly selected within the possible values for the hurricane model parameters $\mathbf{x}$. Over the entire domain, the average prediction error standard deviation σ_{ε_i} is 0.32 m for the significant wave height and 0.11 m for the still water level, but both these quantities vary significantly over the region of interest. The corresponding values for the average mean error are 3.5% and 7%, respectively, which indicate high accuracy of the established approximation.

Figure 5 shows a comparison for the significant wave height predictions for the response surface surrogate model and the high-fidelity numerical model. The comparison between parts (a) and (b) of the figure shows very good agreement, which validates the accuracy of the established surrogate modeling. It should be noted that the cost of the surrogate model for a single evaluation is at least 10^7 times less expensive than the high fidelity models, which is what allows it to be used for real time prediction on a PC.

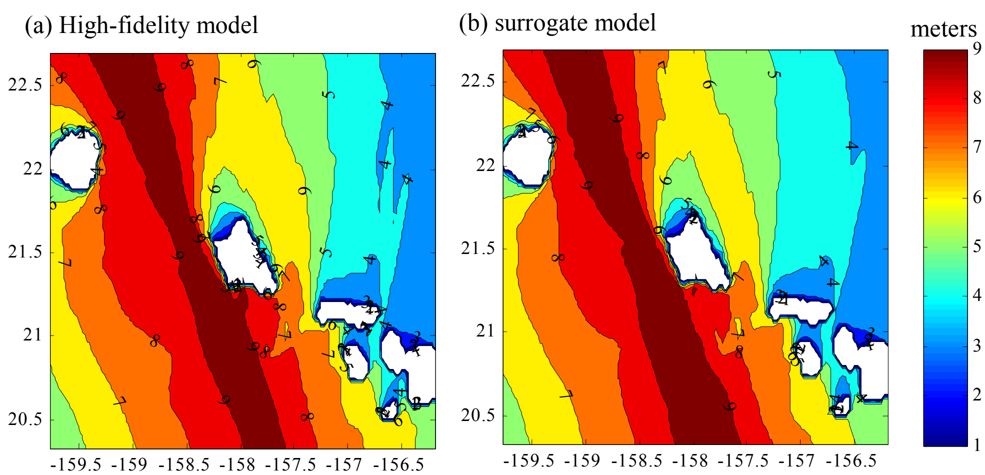

Figure 5: Significant wave height contours for a single hurricane track; comparison between surrogate and high-fidelity models

Risk assessment

The established response surface surrogate model can be then used to predict the response, in particular the still water level and significant wave height, for any desired hurricane scenario and *simultaneously* for all locations of interest around the island. The aforementioned interpolation scheme can then be used to additionally calculate the wave breakup for each transect using as input these two predictions. A sample implementation is presented for a hurricane approaching landfall to Oahu (42 hours before landfall) in Figures 6-8.

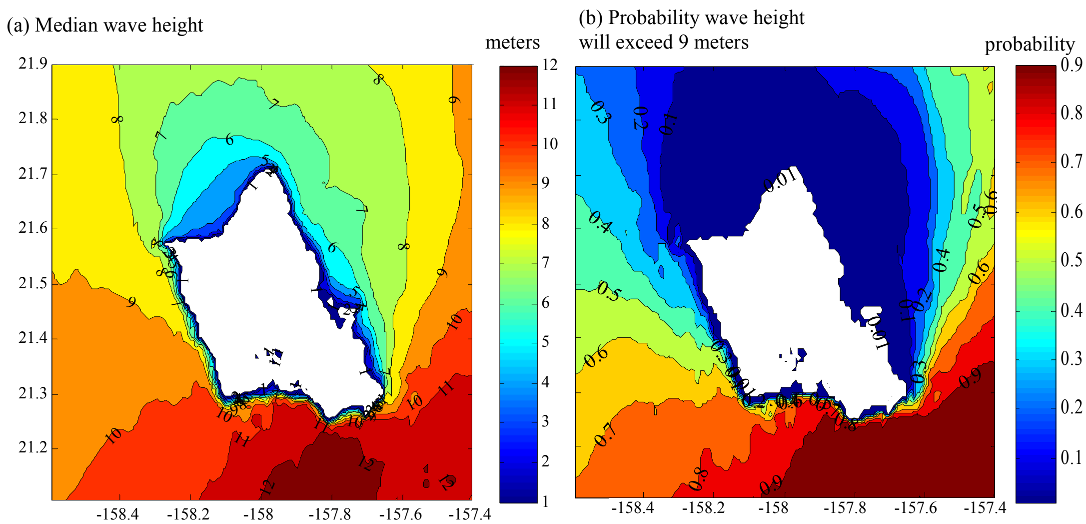

Figure 6: Sample results for risk assessment implementation for wave height

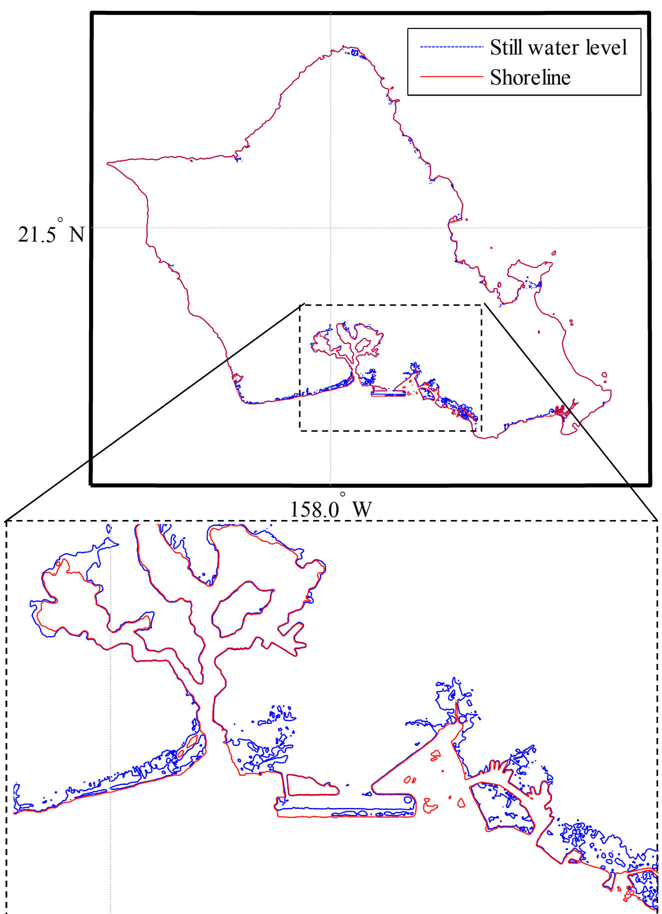

Figure 7: Still water level (SRL) contours with 10% probability of exceedance around Oahu, with magnification of Pearl Harbor and airport region.

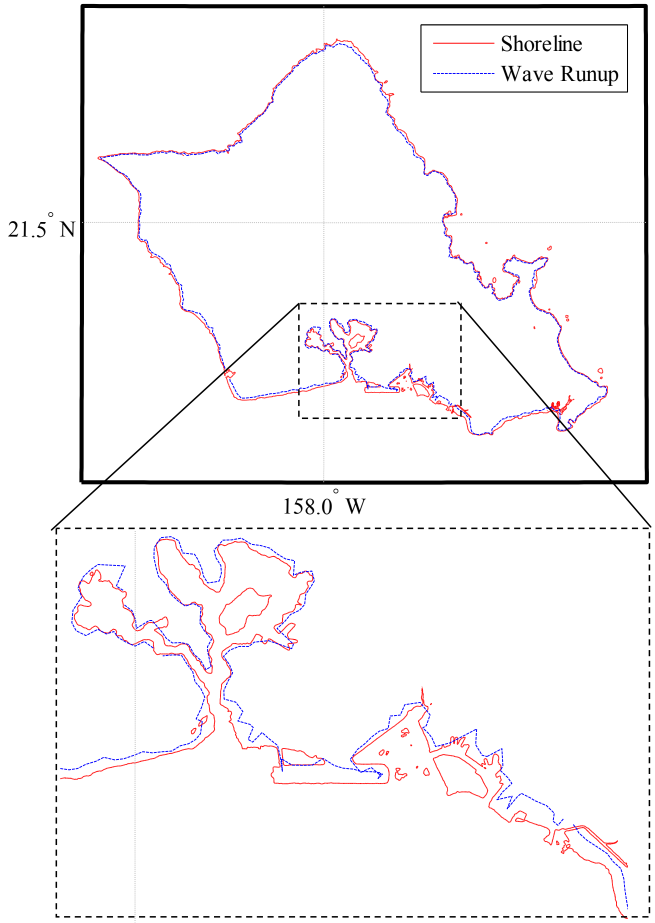

Figure 8: Wave runup level (WRL) contours with 10% probability of exceedance around Oahu, with magnification of Pearl Harbor and airport region.

The characteristics of the hurricane for this sample risk assessment implementation are actually the ones depicted in the GUI in Figure 3. The mean values for hurricane parameters are

$$\mathbf{x}_{mean} = [158.12^o \quad 205^o \quad 950\text{mbar} \quad 16\text{knots} \quad 45\,\text{mbar}] \qquad (13)$$

For defining $p(\mathbf{x})$ these parameters are assumed to follow independent Gaussian distributions with standard deviation selected based on prediction errors for time until landfall equal to 42 hours.

$$\sigma_{\mathbf{x}} = [0.28^o \quad 17.5^o \quad 10.5\text{ mbar} \quad 3.5\text{ knots} \quad 2.5\text{ km}] \qquad (14)$$

Figures 6 shows the median wave height and the probability that the wave height with exceed 9 meters. Figures 7 and 8 show, respectively, the SWL (still water level) and WRL (wave runup level) contours around Oahu with 10% probability of exceedance.

For automated implementation of this risk estimation, a stand-alone tool is developed, as shown in Figure 3. N=2000 evaluations of the surrogate model are used for the stochastic simulation of Equation (5) [thus facilitating a small coefficient of variation (6) and high accuracy estimates for the probabilistic integral (3)]. The total time needed for this risk assessment is 4 min on a 3.2 GHz single core processor with 4 GB of RAM. This corresponds to a tremendous reduction of computational time compared to the high-fidelity model, which required over 1500 hours for analysing a single hurricane scenario, and ultimately is the foundation that allows for the real-time risk assessment described here. The outputs from the risk estimation are graphically presented as contours for the surge and wave runup inundation around the island as well as contours for the significant wave height in the region around Oahu, as shown in Figures 6-8.

CYBER-INFRASTRUCTURE FOR FURTHER SUPPORT OF INITIATIVES

Undoubtedly, research advances and our knowledge of hurricane hazards and their impacts are rapidly evolving, but are often not effectively harnessed in a manner that leverages the intellectual and computational resources and cyberinfrastructure being developed across the country. The automated risk assessment tools developed in this study aimed to bridge this gap. To further promote this task, the University of Notre Dame recently started a new initiative called CYBER-EYE: A Cyber-Collaboratory for National Risk Modeling and Assessment to Mitigate the Impacts of Hurricanes in a Changing Climate (Kijewski-Correa et al. 2012). Figure 9 demonstrates the concept and the preliminary development trajectory. The goal is to establish a virtual organization built around a cyber-enabled computational framework that synergizes existing models, simulation tools and risk assessment methodologies to assess the impacts of hurricanes. The automated risk assessment tool discussed in this study (Figure 3) serves as the preliminary prototype for the effort. Furthermore, instead of attempting to replicate the intellectual infrastructure of competing institutions focused on various aspects of hurricane risk reduction, the approach taken is to leverage the resources and knowledge of these peers in an innovative way. In fact, this approach is entirely consistent with the recent calls by the National Weather Service (NWS) and NOAA for interoperable systems and collaborative tools and workflows (Cline 2009), as well as the UN Second Session of the Global Platform on Disaster Reduction in Geneva (June 16-17, 2009), who called for enhanced knowledge/technology transfer through cyberinfrastructure. A secondary benefit of this cyber-enabled approach will be the capability for engagement of wide ranging stakeholders, through employment of web-based, user friendly interfaces that open far greater potentials for dissemination and engagement (as shown in Figure 9).

The introduction of CYBER-EYE represents an effort to pool and integrate resources in the spirit of collaboration to maximize the impact of all the investments made not only by the University of Notre Dame but by others in the field. As we move along the development trajectory, the goal is to enhance the platform capabilities to maximize the benefit to end users in the virtual coast. As such, the portal will eventually transition to a Big Map Board (BMB) and will adopt a prototype system for "teleconferencing over maps" to provide a virtual conference room with a shared maps, drawing tools, and continual real-time updates (Kijewski-Correa et al. 2012).

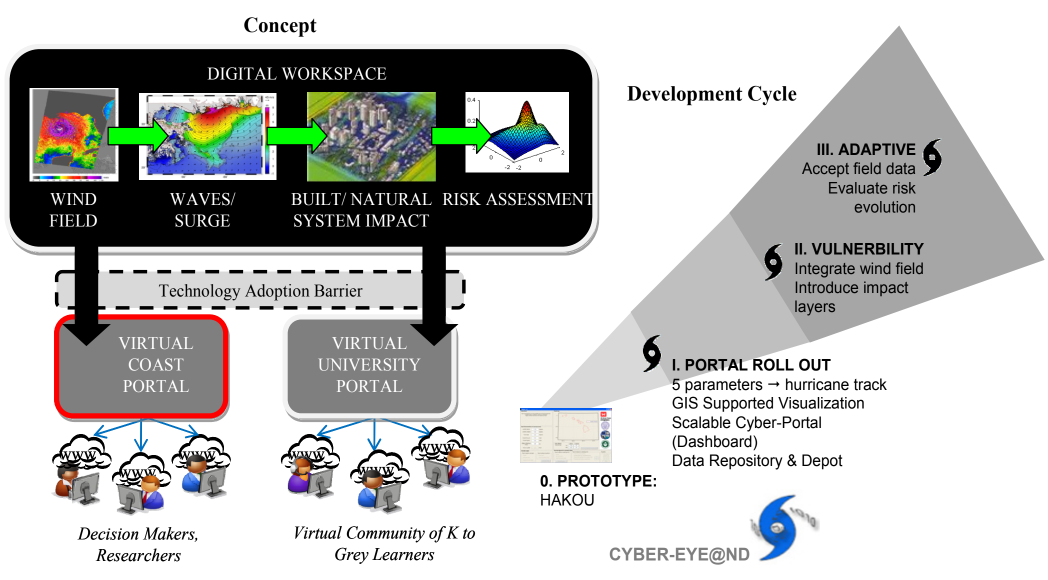

Figure 9: CYBER-EYE concept and development trajectory.

CONCLUSSIONS

A probabilistic framework has been developed here for hurricane risk estimation with particular emphasis on real-time risk evaluation. This methodology uses hundreds of high fidelity model runs, an efficient surrogate model that reproduces well the high fidelity model, and a description of uncertainty to estimate wave, water level and runup probabilities at a much reduced computational cost. The framework is efficient enough that it may easily be used for prediction of risk as a hurricane approaches landfall. However, there is a large up-front computational cost to evaluate the high-fidelity models. As an illustrative example, implementation of hurricane risk estimation for the island of Oahu in Hawaii is presented. In this stand-alone tool, the interface provided to the user requires only a basic understanding of the five parameters used for the simplified description of each hurricane scenario. Results demonstrate the versatility of the proposed approach for creating efficient tools that are simple enough to cross over technology adoption barriers. The total time needed for risk assessment using the developed standalone tool is 4 min on a 3.2 GHz single core processor with 4 GB of RAM. High accuracy is established for the risk estimates as the coefficient of variation for that estimate using 2000 sample runs is very small.

This framework may be readily applied to other regions and other problems where high fidelity model runs may be run in advance but risk estimates are required in real-time. This methodology may also be readily extended to include derivative products such as building and infrastructure damage during a storm, or loss estimates. Current initiatives at the University of Notre Dame to further support these effort were also briefly reviewed.

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APPENDIX A

This Appendix provides further details on the response surface surrogate modeling. The coefficients $\mathbf{a}_i\{\mathbf{x}\}$ for the surrogate model (7) are calculated by initially evaluating $z_i(\mathbf{x})$ in a set of $NS>NB$ hurricane scenarios (called support points for the surrogate model) $\{\mathbf{x}_I;\ I=1,\ldots,NS\}$, and then by minimizing the mean squared error over these points between $z_i(\mathbf{x})$ and the approximation established through Equation (7) (Myers and Montgomery 2002). In the Moving Least Squares (MLS) approach the coefficients are dependent on $\mathbf{x}$, and are selected by minimizing a weighted sum of squared error, with weights that are a function of $\mathbf{x}$ (Taflanidis 2012)

$$J_R\{\mathbf{x}\} = \sum_{I=1}^{NS} w\{\mathbf{x}\}\left[\hat{z}_i(\mathbf{x}_I) - z_i(\mathbf{x}_I)\right]^2 = \left[\mathbf{B}\mathbf{a}_i\{\mathbf{x}\} - \mathbf{F}_i\right]^T \mathbf{W}\{\mathbf{x}\}\left[\mathbf{B}\mathbf{a}_i\{\mathbf{x}\} - \mathbf{F}_i\right] \quad (15)$$

where the following quantities have been introduced

$$\begin{aligned} &\mathbf{B} = \left[\mathbf{b}(\mathbf{x}_1)\ldots\mathbf{b}(\mathbf{x}_{NS})\right]^T;\ \ \mathbf{F}_i = \left[z_i(\mathbf{x}_1)\ldots z_i(\mathbf{x}_{NS})\right]^T \\ &\mathbf{W}\{\mathbf{x}\} = diag\left[w\left(d(\mathbf{x};\mathbf{x}_1)\right)\ldots w\left(d(\mathbf{x};\mathbf{x}_{NS})\right)\right] \end{aligned} \quad (16)$$

and $w\{d(\mathbf{x};\mathbf{x}_I)\}$ is a weight function that depends on the distance d between the point $\mathbf{x}$ for which the approximation is established and each of the support points

$$d(\mathbf{x};\mathbf{x}_I) = \sqrt{\sum_{j=1}^{n_x}\left(\mathbf{x}_j - \mathbf{x}_{j,I}\right)^2 v_j^2} = \sqrt{\left[\mathbf{v}\left(\mathbf{x}-\mathbf{x}_I\right)\right]^T \mathbf{v}\left(\mathbf{x}-\mathbf{x}_I\right)};\quad \mathbf{v} = diag(v_1 \ldots v_{n_x}) \quad (17)$$

with v_i representing the relative weight for each component of x_j (Taflanidis 2012). The introduction of the weights $w\{d\}$ aims at reducing the approximation error at each point by performing a weighted local averaging of the information obtained by the support points that are closer to it. Without these weights, the coefficient vector, $\mathbf{a}_i$, would be constant over the whole domain for $\mathbf{x}$ which means that a global approximation would be established (global least squares). The efficiency –i.e, fit to $z_i(\mathbf{x})$– of global approximations depends significantly on the selection of the basis functions, which should be chosen to resemble $z_i(\mathbf{x})$ as closely as possible. Such a selection is not always straightforward. The MLS circumvents such problems by establishing a local approximation for $\mathbf{a}_i\{\mathbf{x}\}$ around each point in the interpolation domain. This leads to a smaller dependence of the fit on the type of basis functions used (Breitkopf et al. 2005). On the other hand the efficiency of the MLS interpolation depends on the weighting function chosen. This function should prioritize support points that are close to the approximation point, and should vanish after an influence radius D_d. This radius should be selected so that a sufficient number of neighbouring supporting points are included to avoid singularity in the solution for $\mathbf{a}_i\{\mathbf{x}\}$. This means that D_d should include at least NB points. As weighting function in this study the exponential type of function

$$w\{d\} = [e^{-\left(\frac{d}{cD}\right)^{2k}} - e^{-\left(\frac{1}{c}\right)^{2k}}] / [1 - e^{-\left(\frac{1}{c}\right)^{2k}}] \text{ if } d < D_d \qquad (18)$$
$$= 0 \text{ else}$$

is selected, with c=0.4 and k=1 (Gaussian). The relative weights v_i ultimately define the moving character of the approximation within the different directions in the X space and should be chosen to i) establish a normalization for the different components of $\mathbf{x}$ but more importantly ii) provide higher importance for components that have larger influence on the values of $z_i(\mathbf{x})$ (Taflanidis 2012).

Finally the minimization of Equation (15) is a standard quadratic optimization problem and yields

$$\begin{aligned} &\mathbf{a}_i\{\mathbf{x}\} = \mathbf{M}^{-1}\{\mathbf{x}\}\mathbf{L}\{\mathbf{x}\}\mathbf{F}_i \text{ where} \\ &\mathbf{M} = \mathbf{B}^T\mathbf{W}\{\mathbf{x}\}\mathbf{B} \text{ and } \mathbf{L}\{\mathbf{x}\} = \mathbf{B}^T\mathbf{W}\{\mathbf{x}\} \end{aligned} \qquad (19)$$

Ultimately D_d in Equation (18) should be selected so that $\mathbf{M}$ is invertible. Finally Equation (7) yields

$$\hat{z}_i(\mathbf{x}) = \mathbf{b}^T(\mathbf{x})\mathbf{M}^{-1}\{\mathbf{x}\}\mathbf{L}\{\mathbf{x}\}\mathbf{F}_i \qquad (20)$$

The fit of the response surface approximation may be judged by selecting a number of hurricane scenarios to represent the validation points (control points), denoted by $\mathbf{x}_p$; p=1,…,N_E , and then evaluating the mean error ME, given by (Myers and Montgomery 2002)

$$ME = \sum\nolimits_{p=1}^{N_E} | z_i(\mathbf{x}_p) - \hat{z}_i(\mathbf{x}_p) | / \sum\nolimits_{p=1}^{N_E} | z_i(\mathbf{x}_p) | \qquad (21)$$

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