# SURROGATE MODELING OF STORM RESPONSE

Jeffrey A. Melby, Noble Consultants-G.E.C. Inc., <u>jmelby@nobleconsultants.com</u> Alex Taflanidis, Notre Dame University Norberto Nadal-Caraballo, U.S. Army Engineer R&D Center Victor Gonzalez, U.S. Army Engineer R&D Center Fatima Diop, Noble Consultants-G.E.C. Inc.

## INTRODUCTION

Surrogate models are yielding simple, fast and accurate storm response predictions. Surrogate modelling is being applied to compute regional response or compute thousands of realizations in seconds. These tools are useful for forecasting, scenario analysis and risk assessments.

Approaches used for coastal application include artificial neural networks (ANN), Gaussian process regression (Kriging), and response surface techniques (e.g. Kim et al. 2015, Jia et al. 2013,). These previous approaches were limited to hurricane suites that were already optimally preconfigured using joint probability methods. The results were surprisingly effective in large part because the simulation suites were already optimized and the high dimensional parameter space was well correlated in time and space.

The kriging method was applied for the study reported here to 1. Optimize the parameter space and resulting selection of storms for high fidelity modelling, and 2. Construct surrogate models for both extratropical and tropical storm suites and for wave transformation as well as hurricane surge and other hurricane responses. The results were used for forecasting, scenario analysis, and risk assessments.

#### APPROACH

Surrogate models for hurricane storm surge time series prediction using kriging have been reported previously. These techniques used high fidelity surge modelling for most of the Gulf of Mexico and the Virginia to Maine regions. The surrogate models were trained using tropical storm parameters (latitude, longitude, central pressure, radius to maximum wind speed, storm heading, and forward speed) and individual responses (e.g. surge). The kriging methods accurately reproduced both peaks and time series of responses. The surrogate models provided accurate reproduction of historical events.

Herein, we apply the kriging methods to define the storms for training the kriging model. In addition the methods are used for wave transformation. An extensive validation was conducted to determine the optimal application of the kriging approach. In this paper we will report the surrogate training and validation techniques and results.

### SOME RESULTS

The wave transformation was conducted at Coos Bay, Oregon from Wave Information Study point 83032 to the inlet. Simulation of significant storms was conducted using the phase averaged wave transformation model CMS-wave. A peaks-over-threshold screening method was used to identify significant storms. The top 20 historical storms and several thousand synthetic storms were transformed spanning the historical range of wave height  $H_{n0}$ , wave period  $T_{p_i}$  wave mean direction and water level. In the initial suite of storms, tidal currents were included in the top 20 historical storm simulations but not in the synthetic suite.

A surrogate model was trained on an initial set of 20 synthetic events selected at random from the large simulation suite. Design of experiments techniques were successively applied to create a surrogate that minimized the number of CMS-Wave simulations while minimizing the surrogate model error. Offshore  $H_{m0}$ ,  $T_{p}$ , and wave mean direction and nearshore water level were used as inputs and nearshore transformation coefficients for  $H_{m0}$ ,  $T_{p_{1}}$  and mean direction were outputs. Results in the form of wave height transformation coefficient are shown in Figure 1 for four representative storms.  $K_t$  for the CMS-Wave simulations is plotted on the horizontal axis while  $K_t$ on the vertical axis is from the kriging prediction. There are 84 of the total spatial 353 points plotted in Figure 1. The points span the region from outside the Coos Bay inlet to inside. The kriging training took about 7 minutes for 353 points in and around the inlet. Areas where tidal currents were large tended to produce greater errors because tidal currents were not included in the synthetic training storms.

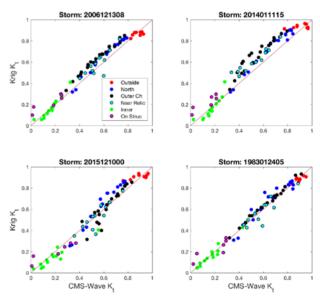


Figure 1. Kiging wave height transformation for Coos Bay Oregon

The kriging model was used for risk assessment. Simulation of 1000 life cycles of 50 years each was completed in less than 1 minute.

## REFERENCES

Jia, G., Taflanidis, A.A., Nadal-Caraballo, N.C., Melby, J.A., Kennedy, A.B., Smith, J.M., (2015). "Surrogate modelling for storm surge prediction using an

existing database of synthetic storms; addressing time-dependence of output and implementation over an extended coastal region," Paper accepted for publication in Natural Hazards.

Kim, S.-W., Melby, J.A., Nadal-Caraballo, N.C., and Ratcliff, J. (2015). "A time-dependent surrogate model for storm surge prediction based on an artificial neural network using high-fidelity synthetic hurricane modelling." Natural Hazards, 76(1), 565-585