COMPUTATIONAL SIMULATION SET SELECTION FOR STORM SURGE SURROGATE MODELING

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INTRODUCTION

Flooding by tropical cyclones poses a significant threat to life and livelihood in coastal communities worldwide. Recent advances in machine learning have enabled efficient estimation of tropical cyclone surge using surrogate models (e.g., Kajbaf & Bensi 2020 and refs therein). In turn, the application of these surrogate models supports the probabilistic hazard characterization and flood warning essential for prosperity in the coastal zone. Typically, storm surge surrogate models are developed from discrete sets of high-fidelity storm surge simulations with physics-based models such as ADCIRC (e.g., Westerink *et al.*, 2008). Herein, we explore the significance of storms represented in these physics-based simulation sets–hereafter training sets–as they relate to the performance of storm surge surrogate models.

METHODS

While many approaches for storm surge surrogate model development exist, here we consider a simple approach using multilinear interpolation and a more complex approach using artificial neural networks (ANN). To test surrogate model performance using various sampling methods, we assume an analytical, idealized surge response surface based on five storm track parameters:

$$\eta = f_x\, f_{\Delta p}\, f_R\, f_\theta\, f_v \qquad (1)$$

where x is storm landfall location, $\Delta\mathrm{p}$ is central pressure, R is storm radius, θ is heading and v is forward speed. The simplest analytical model assumes all functions f are linear with respect to their track parameter, except f_x which is taken to be triangular with x (piecewise linear); this simple model is based on the natural structure of tropical cyclone surge (e.g., Irish *et al.* 2008).

We consider several different approaches for developing storm sets: (1) Staggered-grid sampling, (2) Random sampling (Latin hypercube), (3) Samples selected because of their likelihood, (4) Iterative sampling starting with staggered set (1), (4) Iterative sampling starting with random set (2). The third storm set type specifically includes publicly available storm surge simulation sets developed for hazard characterization in the United States, which used the joint probability method with storm sampling by Bayesian quadrature (e.g., Nadal-Caraballo *et al.*, 2015). For storm sets (4) and (5), the surrogate models are first developed respectively using set (1) and (2), then additional storms are added in regions of the storm-track parameter space that exhibit large disagreement between the surrogate model and the analytical solution (e.g., Zhang *et al.*, 2018).

Finally, we evaluate surrogate model performance using both aggregate and magnitude-binned statistics along with error visualization, where errors are computed by comparing predictions for a large storm set (>100,000) not in the training set with the analytical solution by Eq. 1.

PRELIMINARY RESULTS

Figures 1 and 2 show results respectively when staggered grid and random training sets are used to develop the multilinear interpolator (surrogate model). Results shown compare the analytical values from Eq. 1 with the surrogate model results for 200,000 storms, selected on a staggered grid; storms in the training set are excluded from the results shown (325 storms or less). The results show that the surrogate model tends to underpredict surge as surge magnitude increases. For the analytical case shown, the staggered-grid training sets outperform the random training sets, even for relatively small training set sizes (e.g., panes a when training set size is 275 storms). In all cases, as anticipated surrogate model accuracy improves with increased training set size. Yet, while the staggered-grid training sets achieve a high level of accuracy across all surge magnitudes with training set size > 4,000, the random training sets continue to exhibit significant error and continue to underpredict. In the presentation, we expand on these preliminary results to include different analytical forms of Eq. 1, to explore potential benefits of iterative sampling, and to compare models by multilinear interpolation and by ANN.

REFERENCES

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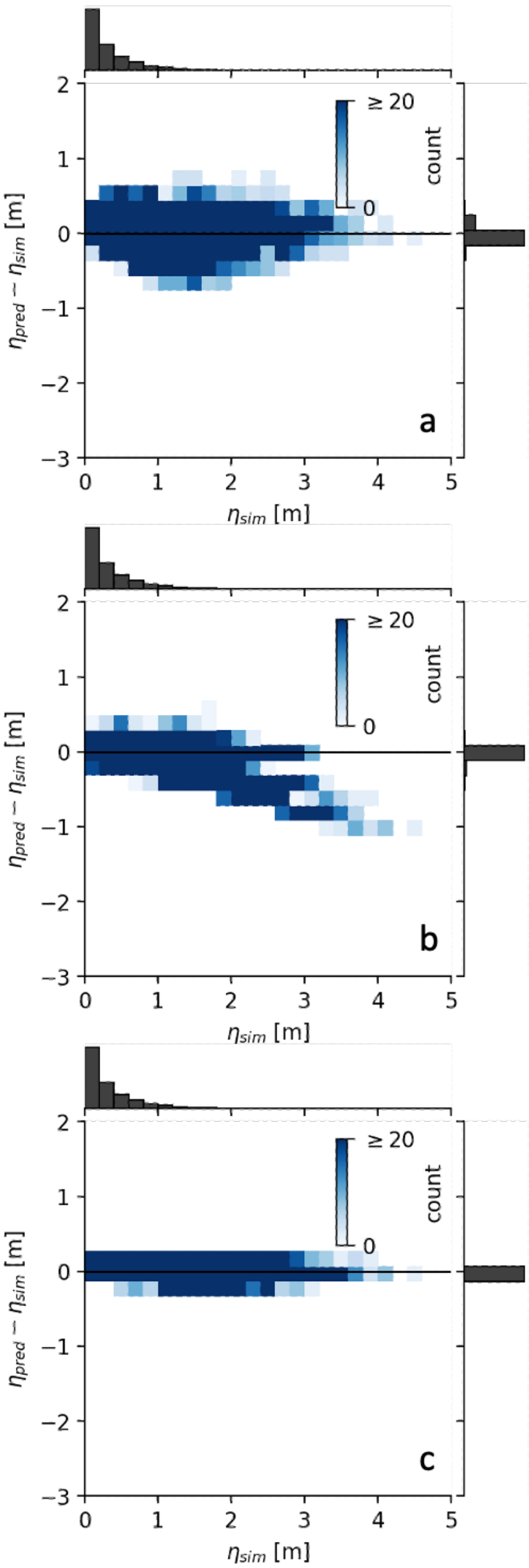

Figure 1 - Surge by Eq. 1 (sim) vs. surge by multilinear interpolation (pred) from staggered grid training sets with 483 (a), 1,267 (b), and 4,149 (c) storms. Analytical and interpolated estimates shown for about 200,000 storms.

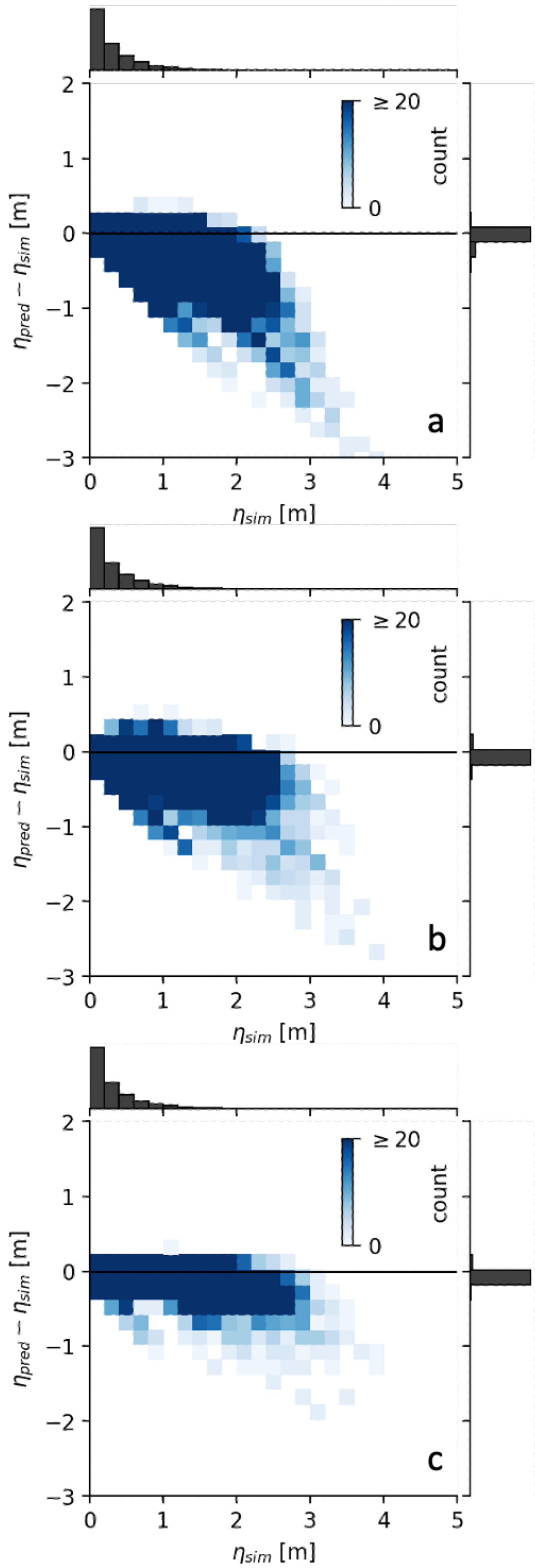

Figure 2 - Surge by Eq. 1 (sim) vs. surge by multilinear interpolation (pred) from random training sets with 483 (a), 1,267 (b), and 4,149 (c) storms. Analytical and interpolated estimates shown for about 200,000 storms.