Data-Driven Boundary Correction and Optimization of a Nearshore Wave and Hydrodynamic Model to Enable Rapid Environmental Assessment

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LONG-TERM GOALS

The present project is part of a comprehensive effort by the PI, his students, and collaborators at the Naval Research Laboratory to increase the robustness and viability of the Delft3D model suite as an operational forecasting tool, and aid its continued transition to Navy forecasting centers. Prior projects have focused on determining the model's response to characteristics and sample sizes of bathymetric information. The present project focuses on determining the effect of boundary errors on model response, and the development of methods to ameliorate these issues. These boundary errors arise when the numerical grid for the forcing condition (wave model) is is insufficiently extended in the lateral (longshore) direction relative to the numerical grid for the current (flow model).

OBJECTIVES

The primary objective of this work is to investigate the effect of boundary forcing errors on the model response. This has a direct impact on the use of Neumann lateral boundary conditions, since these errors arise from insufficient extension of the WAVE (SWAN) grid beyond the lateral boundaries of the FLOW grid. There is a balance between accuracy and computational efficiency that must be struck; the computational bottleneck in the Delft3D system is SWAN, the wave model, and the run time increases with lateral extent of the WAVE grid. While point-by-point comparisons between model and data for various WAVE grid extensions can offer a view of the dependence of accuracy on grid extension, it does not yield any information on the spatial characteristics of the solution; poor data-model comparison could be the result of slight spatial mismatches of highly variable solution fields, or oversmoothed solutions which have little relevance to the physics at hand.

APPROACH

Among the recent enhancements to the utility of the Delft3D model for nearshore process simulation include the implementation of Neumann lateral boundary conditions (Roelvink and Walstra 2004), which allow for flow to enter and leave the lateral boundaries with no artificial circulation. This boundary condition is formulated by reducing the flow equations in the hydrodynamic model to a single dimension, which has the effect of setting conditions on the *gradient* of the velocities rather than on the velocities themselves. For wave-induced flow, however, one consequence is the need to have a wave-model grid that is significantly wider than the hydrodynamic model grid; this is done in order to keep irregularities in the forcing away from the boundaries of the hydrodynamic model. However, SWAN, the wave model for Delft3D, requires significant iterative steps, and as such is a computational chokepoint for forecast turnaround. One of our primary goals in this project is to evaluate the errors as a function of the lateral grid extent.

One aspect of the error analysis we are investigating is the effect of reducing the lateral extent of the wave model domain. We first analyze the effect that small deviations from complete satisfaction of the Neumann boundary condition have on the hydrodynamic predictions. This is done first by perturbing the equations describing the lateral boundary condition by a small error, and examining the growth or decay of that error, analogous to Chen and Svendsen (2003) for the case of errors in the flow velocity at the boundary. We then indirectly impose a deviation from the satisfaction of the zero Neumann boundary condition by incrementally shortening the lateral extent of the wave model grid, and determining the effect on the model results. The analysis of the error will require some method of looking at the multi-dimensional tendencies of the error and some estimation of the scales most vulnerable to error, rather than just the deviation between model and data. To this extent, we use spatio-temporal analysis methods such as Empirical Orthogonal Function (EOF) analysis to determine the overall scales of motion in the flow field and the extent of the variation of their response to the errors.

Personnel consists of the PI and his Ph.D. student Ms. Samira Ardani (B.S. and M.S., Department of Civil Engineering, K.N. Toosi University of Technology, Tehran, Iran). We have used Bayesian methods coupled with Markov chain Monte-Carlo methods to determine the effect of model setup errors and bathymetric resolution on the model results.

WORK COMPLETED

We have implemented a Markov chain Monte Carlo scheme to discern both the "best" set of parameters which allow the model to best-fit measured data, but also provides the statistics for quantifying undertainty. The overall workflow is shown in Figure 1.

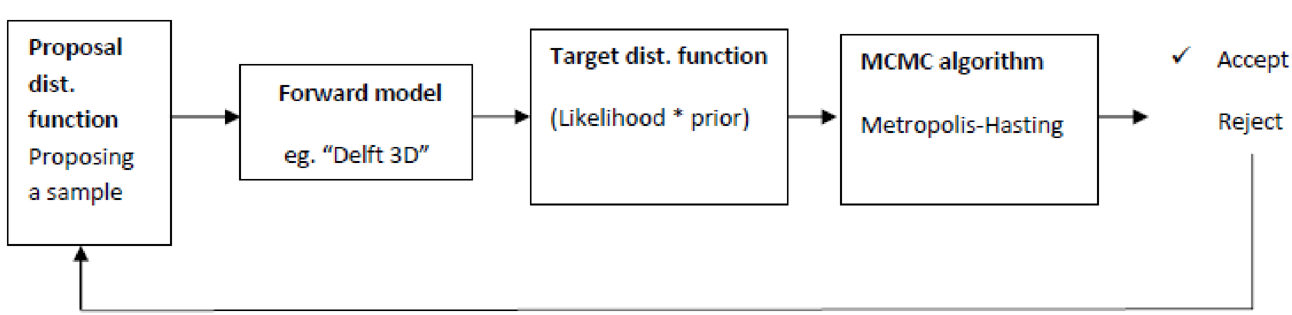

Figure 1. Workflow for Markov chain Monte Carlo scheme.

The two parameters under study are user-defined and involve key inputs to the Delft3D model – the bathymetry and the grid configuration. The optimum values of these parameters are sought in order to best fit data from the Duck94 (Birkemeier and Thornton 1994) experiment, conducted at the U.S. Army Corps of Engineers Field Research Facility at Duck, NC.

Bathymetry for the area was measured at discrete points and interpolated to a particular grid. Interpolation can be performed using smoothing scales (Plant et al. 2002), which govern the overall smoothness of the resulting bathymetry. We used the smoothing scale interpolator of Plant et al. (2002) to specify longshore and cross-shore smoothing scales and determine the set of scales which lead to best results.

The grid setup is manifested in this study as a relationship between the width of the wave model (SWAN) grid and the hydrodynamic model (FLOW) grid. The SWAN model can be a computational bottleneck, particularly when run in stationary mode and tight iteration criteria are specified (Jiang and Kaihatu 2011). This would compel a SWAN grid with a small longshore extent, perhaps the same size as the underlying FLOWgrid. However, when using the model to run nearshore currents, the Neumann boundary conditions in FLOW are often specified to allow circulation egress through the lateral boundaries. These require the longshore gradient of the forcing to be close to zero, and would thus engender a longer SWAN grid. As there are no established guidelines, we define a ratio of the longshore extent of the two grids as an input metric for user specification. Jiang and Kaihatu (2011) show the effects of this determination on the model results from Delft3D. This "grid ratio" is also used herein as an optimizable quantity. One challenge of this is that the errors would tend to uniformly decrease with increasing grid ratio, rather than forming a minimum in the error surface; there is nothing presently in the algorithm which would prevent it from eventually selecting the largest ratio. Redesign of the optimization algorithm would need to incorporate another metric as an additional constraint.

The work thus far has used only a small range of incident wave conditions for the analysis. Further work has begun in performing similar analyses with respect to the temporal variation of the incident wave condition over a wide time interval.

RESULTS

The wave conditions for October 23, 1994 were used to determine the most favorable longshore and cross-shore smoothing scales using Bayesian statistics. Field measurements for the time were used to guide the system toward the optimum set of scales. Figure 2 shows the area, with bathymetric survey locations and hydrodynamic measurement locations.

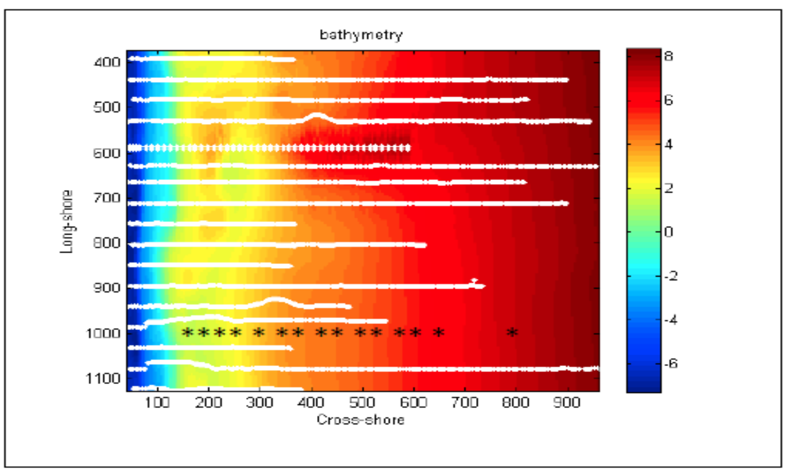

Figure 2. Locations of bathymetric measurements (white) and hydrodynamic measurements (black) for Duck, NC., plotted over a highly-resolved interpolation of the bathymetric measurements.

The Markov chain Monte Carlo algorithm was used to determine the consequent smoothing scales based on prior estimates of likelihood. The smoothing scales are used to generate the bathymetry, and Delft3D run over this generated bathymetry. The results are compared to measurements of longshore velocity and waveheight at the measurement locations. Based on these comparisons, the samples are either rejected or accepted depending on the probability of the prior estimate in the iteration chain. Eventually a probability of occurrence of the accepted samples is generated. Figure 3 shows the histogram of the smoothing scales accepted in the Markov chain Monte Carlo method. We see that a peak in this histogram for the cross-shore scale (left) occurs around 50 m, and the peak for the longshore smoothing scale (right) occurs around 190 m. This indicates that a bathymetric field resulting from interpolation with either of those smoothing scales is the most likely to have been present at the time oof the hydrodynamic measurements, since they provide the smallest error when compared to measurements.

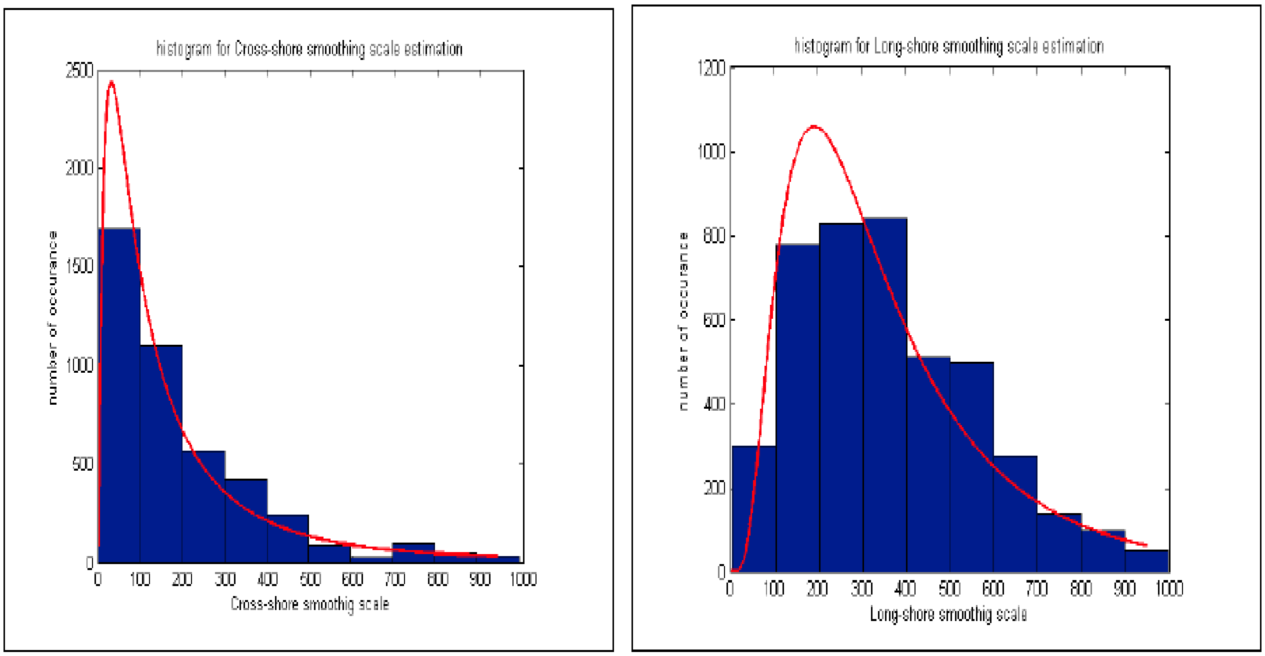

Figure 3. Smoothing scale histograms, with fitted log-normal distributions. Left: Cross-shore scale. Right: Longshore scale.

The above histograms were developed independently. A joint probability of smoothing scales can also be determined, which provides both best-fit scales. This joint probability, and the associated bathymetry, are shown in Figure 4.

The significance of these results is centered on the problem of determining sufficient input for a model – particularly if that input (such as bathymetry) is difficult and time-consuming to measure. In line with our previous work with genetic algorithms (Manian et al., 2011), we are developing a methodology for determining the amount of information a model requires for optimal accuracy.

IMPACT/APPLICATIONS

This work can help streamline data gathering missions for forecast model operations. Bathymetry, for example, is laborious to measure, and in many cases it is not clear how much information is required for the model to respond realistically. As Plant et al. (2009) noted, all models assume some averaging over space and time and are not able to respond to all features of the bathymetry. By using the model's response to help guide the survey, we can compress the time needed for adequate input to be provided for operational models.

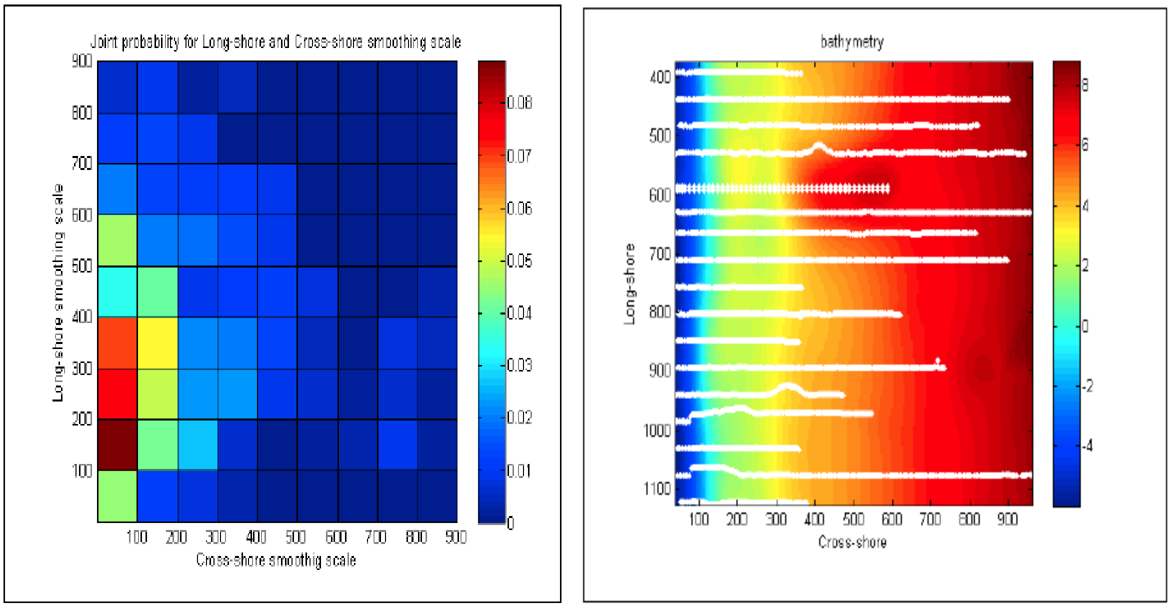

Figure 4. Joint probability of smoothing scales for bathymetric interpolation (left) and resulting bathymetric field (right). Location of bathymetric measurements shown in white. This is the bathymetry most likely to have occurred when the measurements were taken.

RELATED PROJECTS

None

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