



The effect of bathymetric filtering on nearshore process model results

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ARTICLE INFO

Article history:

Received 1 February 2008

Received in revised form 28 October 2008

Accepted 29 October 2008

Available online 4 December 2008

Keywords:

Prediction

Wave height

Alongshore current

Rip current

Interpolation

Errors

ABSTRACT

Nearshore wave and flow model results are shown to exhibit a strong sensitivity to the resolution of the input bathymetry. In this analysis, bathymetric resolution was varied by applying smoothing filters to high-resolution survey data to produce a number of bathymetric grid surfaces. We demonstrate that the sensitivity of model-predicted wave height and flow to variations in bathymetric resolution had different characteristics. Wave height predictions were most sensitive to resolution of cross-shore variability associated with the structure of nearshore sandbars. Flow predictions were most sensitive to the resolution of intermediate scale alongshore variability associated with the prominent sandbar rhythmicity. Flow sensitivity increased in cases where a sandbar was closer to shore and shallower. Perhaps the most surprising implication of these results is that the interpolation and smoothing of bathymetric data could be optimized differently for the wave and flow models. We show that errors between observed and modeled flow and wave heights are well predicted by comparing model simulation results using progressively filtered bathymetry to results from the highest resolution simulation. The damage done by over smoothing or inadequate sampling can therefore be estimated using model simulations. We conclude that the ability to quantify prediction errors will be useful for supporting future data assimilation efforts that require this information.

Published by Elsevier B.V.

1. Introduction

Nearshore process models are capable of predicting both wave evolution across the nearshore region as well as the associated wave and wind driven nearshore currents (Booij et al., 1999; Reniers et al., 2007). Required input to this modeling approach includes estimates of water levels, wind, and a spectral description of the waves on the open boundaries as well as the bathymetry at all modeled locations. Our ability to describe these inputs is only as good as the technology used to measure and interpret them. For example, bathymetry is typically surveyed at discrete spatial locations and times as the data density is limited by the amount of time required to conduct the survey or to time periods where marine weather conditions permit survey operations. Bathymetric data will tend to be sparsely sampled in either space or time, and, therefore, it must be interpolated in order to fully populate model domains.

Furthermore, there is a potential (if not certain) mismatch between the scales that we wish to resolve with the nearshore process model (e.g., beach cusps, crescentic bars, and rip channels) and the scales that are resolved by the survey data (which may be higher or lower resolution than required, Plant et al., 2002). This mismatch is usually addressed through numerical treatment of the data (interpolation) or

the model (adjust grid resolution) or both. It is not clear which method or combination of methods yields the best model predictions. And, it is not clear that the optimal bathymetry for a particular wave model is also the optimal bathymetry for a corresponding flow model.

If we focus on the problem of providing bathymetry to a nearshore process model, then we would like to be able to objectively specify an optimal survey design to appropriately support a specific model resolution. This assumes that the important scales of variability have been selected by the modeler or model forecast user. Different users would likely have different requirements concerning the resolved scales in the model predictions. For instance, for public safety it might be important to resolve rip currents at hourly intervals with spacing of tens to hundreds of meters while for land-use management it might be important to resolve shoreline variations over years and decades spanning distances of tens to hundreds of kilometers. Using the model design as a constraint, the question becomes “what are the smallest spatial scales that a bathymetric survey needs to resolve in order to support an accurate model prediction?”

The answer to this question depends on properties of the environment as well as the model. For instance, if the spatial resolution of a particular model implementation is 10 m-by-10 m (cross-shore and alongshore dimensions), then the model will not resolve features with length scales shorter than 20 m-by-20 m (the Nyquist wave length). If such short scales exist in the real environment, they are assumed to be unimportant and they might need to be filtered out of the bathymetry

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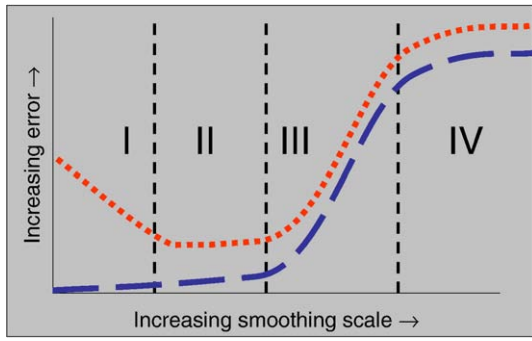


Fig. 1. Idealized model error response to bathymetric smoothing. The dashed curve describes errors due to comparing a model with high-resolution bathymetry to a model with filtered bathymetry. The dotted line describes error between observations and a model with filtered bathymetry. The error regimes I–IV are described in the text.

that is used by the model to prevent aliasing that could lead to model errors. For instance, aliasing can cause short-scale beach cusps to masquerade as larger-scale rhythmic features (Plant et al., 2002). Even if the observations are sufficiently dense to resolve short scale features, there may be model errors if the processes associated with the short features are not accurately parameterized. As an example, the swash flow (and many other details) associated with short-scale beach cusps is not resolved by typical wave-averaged model schemes. Therefore, the beach cusps might need to be filtered out of the bathymetry unless processes associated with unresolved features are added to the model in the form of new parameterizations.

Our present hypothesis is that model errors can be minimized through some amount of bathymetric filtering and that the optimal amount of filtering should depend on the range of spatial scales that are accurately parameterized. Fig. 1 provides a qualitative picture of the effect that short scale variations and smoothing might have on model error. The modeled quantity of interest could be either wave height or flow velocity sampled at one or more locations. Consider a model-data comparison for the situation where the model grid resolution is held constant. Imagine that we have collected bathymetric data that are at much higher resolution than the model grid such that we could directly use surveyed depths at all locations within the model domain, if so desired. Assuming that short scale (compared to the model grid resolution) variations exist in the bathymetric data, we should more appropriately apply some sort of filtering to remove potential aliasing. We can apply a linear filter that takes the form

$$Z_{\text{filt}}(x_i, y_i, t_i) = \sum_j a_{ij} Z_{\text{obs}}(x_j, y_j, t_j), \quad (1)$$

where Z_{obs} is the observed bathymetry at discrete locations x_j, y_j, t_j , and Z_{filt} is the filtered bathymetry evaluated on the model domain (x_i, y_i, t_i). The filter weights take the functional form:

$$a_{ij} = \text{funct.} \left(\left| \frac{x_j - x_i}{L_x} \right| + \left| \frac{y_j - y_i}{L_y} \right| + \left| \frac{t_j - t_i}{L_t} \right| \right), \quad (2)$$

with smoothing scale parameters L_x, L_y , and L_t , where the subscripts x, y , and t correspond to cross-shore, alongshore, and time coordinates, respectively. The larger the smoothing scale, the more the output is filtered.

If the filter scale is much smaller than the distance between survey observations, then only one observation will contribute to the summation in Eq. (1). If the filter scale is also much smaller than the model grid spacing, then the model's bathymetry will include aliasing errors. We label model errors due to aliasing as type-I errors, which result if not enough filtering has been applied to the data. Type-I errors may also result if there is no aliasing, but, instead, the input bathymetry resolves short-scale features and associated processes that are not treated by the model (e.g., swash over beach cusps is not

treated by wave-averaged models). As the filter scale is increased, type-I errors are removed and we expect that the overall model performance will be improved. At this point, we achieve the smallest model errors (type-II errors) because the bathymetry is well matched to the scales that are resolved by the model. In this case, type-II errors reflect intrinsic model deficiencies that are not related to the bathymetry errors. If further smoothing does not affect model errors, then (1) there may be no significant bathymetric variations at these scales or (2) the model is intrinsically insensitive to these variations. At some point, the smoothing begins to remove the features that are important to the model prediction (type-III errors). For instance, sandbars or rip channels might be removed with large cross-shore or alongshore filter scales. Finally, all interesting features are removed at very large filter scales; the bathymetry is replaced by a planar or even horizontal surface, and additional filtering does not inflict much additional damage (type-IV errors).

An understanding of the sensitivity of model prediction errors can be used to identify optimal sampling strategies. Survey data that yield only type-II errors are desired. If the upper limit of the smoothing scale for this error type is known, then survey data need to be sampled to support this amount of filtering. This requires samples spaced about one-half the optimal smoothing scale (Plant et al., 2002).

It is not always possible to design an optimal survey. Then, the relevant question becomes “what damage does a particular survey resolution do to the model predictions?” Again, we have the option to filter the short scale bathymetric features in order to reduce model prediction errors, but important features may not be resolved. Without additional information, the best we can do is to estimate the errors that have crept into the problem. We would like to know what type of errors (types I–IV) will be encountered, and we would like to be able to quantify the error magnitudes. This knowledge can be used, for instance, in a data assimilation strategy. A typical application would be to find an optimal combination of model predictions and sparse in situ observations. For example, if both modeled and observed nearshore currents are available, the observations can be used to update the model prediction via a Kalman filter (Kalman, 1960). Consider assimilation of modeled and observed velocities (U_{model} and U_{observed}):

$$U_{\text{update}} = U_{\text{model}} + K(U_{\text{observed}} - U_{\text{model}}) \\ K = \frac{\sigma_{\text{model}}^2}{\sigma_{\text{observed}}^2 + \sigma_{\text{model}}^2}. \quad (3)$$

Here σ describes model and observation errors. If the model error is relatively large, then K is large, and the updated velocity, U_{update} , is dominated by the observations. The important point is that both model and observation errors are required known in this type of optimal assimilation.

The objective of this paper is to estimate the sensitivity of nearshore hydrodynamic model errors to progressive filtering of the input bathymetry. We are treating the smoothness of the bathymetry as a control variable, much like other studies investigate the sensitivity of model results to the choice of parameterization or parameter value. We estimate errors in prediction of both wave height and mean current vectors and will show observed response to bathymetric smoothing that is consistent with Fig. 1. In Section 2 (Approach) we describe Duck94 (Birkemeier and Thornton, 1994) data collection, data processing, and Delft3D (Lesser et al., 2004) model implementation. In Section 3 (Results) we describe the model data error comparisons evaluated at a number of smoothing scales for several representative cases. We find that the flow and wave height errors have different sensitivity to smoothing and that these errors are predictable. Finally, in section 4 (Discussion and Conclusions) we comment on the implications that the results have on modeling, surveying, and assimilation. The conclusion is that the analysis approach presented here can be used to implement optimal survey

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