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Prediction and assimilation of surf-zone processes using a Bayesian network Part II: Inverse models

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ABSTRACT

A Bayesian network model has been developed to simulate a relatively simple problem of wave propagation in the surf zone (detailed in Part I). Here, we demonstrate that this Bayesian model can provide both inverse modeling and data-assimilation solutions for predicting offshore wave heights and depth estimates given limited wave-height and depth information from an onshore location. The inverse method is extended to allow data assimilation using observational inputs that are not compatible with deterministic solutions of the problem. These inputs include sand bar positions (instead of bathymetry) and estimates of the intensity of wave breaking (instead of wave-height observations). Our results indicate that wave breaking information is essential to reduce prediction errors. In many practical situations, this information could be provided from a shore-based observer or from remote-sensing systems. We show that various combinations of the assimilated inputs significantly reduce the uncertainty in the estimates of water depths and wave heights in the model domain. Application of the Bayesian network model to new field data demonstrated significant predictive skill ($R^2 = 0.7$) for the inverse estimate of a month-long time series of offshore wave heights. The Bayesian inverse results include uncertainty estimates that were shown to be most accurate when given uncertainty in the inputs (e.g., depth and tuning parameters). Furthermore, the inverse modeling was extended to directly estimate tuning parameters associated with the underlying wave-process model. The inverse estimates of the model parameters not only showed an offshore wave height dependence consistent with results of previous studies but the uncertainty estimates of the tuning parameters also explain previously reported variations in the model parameters.

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1. Introduction

Large spatial and temporal variability in waves, water levels, currents, and bathymetry characterizes the nearshore coastal environment. These variables are typically strongly coupled, as can be illustrated using a variety of numerical models. Therefore, accurate predictions of any of these variables require accurate measurements of boundary-condition data, including details of the incident wave spectrum, water level variations, and bathymetry. Numerous studies demonstrate significant model prediction skill when accurate data are available, e.g., SWAN (Simulating Waves Nearshore, Booij et al., 1999; Ris et al., 1999), Delft-3D (Lesser et al., 2004; Reniers et al., 2007), or ADCIRC (Westerink et al., 2008). A modern challenge that must be overcome to use these advanced models for both practical applications as well as for scientific study is to obtain appropriate initial and boundary data from often sparse, noisy, or disparate data sources. In essence, the model capabilities often exceed the quality of the data used to force the models. Numerous approaches to this problem have been implemented using, for instance, spatial interpolation (Plant et al., 2009) or formal data-assimilation methods (e.g., Feddersen et al., 2004). Researchers of global ocean circulation and weather have recognized that data assimilation is a required component of their research and operations (e.g., Goerss, 2009). This recognition has been slower among those studying the shallow regions near the coastline. Here, we demonstrate a new methodology that is appropriate for assimilating data and models that are available in the nearshore environment.

In our companion paper (Plant and Holland, 2011), we presented a Bayesian network approach for making wave-height predictions and associated prediction errors across the surf zone where the network acted as a forward model. The Bayesian network approximates the joint probability between system variables (e.g., wave height, period, direction, and water depth) that were expected to be correlated. A specific system variable can be estimated using constraints on related variables provided by observations or other data. The approach assumed that both the model and the data were potentially inaccurate. Specifically, data inaccuracies (including measurement errors and spatial under-sampling) and model

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inaccuracies were captured in parameter errors. The Bayesian network was trained through the assimilation of realistic simulations provided by a 1-dimensional (cross-shore) deterministic numerical model. When new data inputs and input errors were supplied to make a prediction, the Bayesian approach made skillful predictions of both measured wave heights and prediction uncertainty.

Another capability of the Bayesian network approach, not described in the companion paper, is that it may be applied in an inverse sense. That is, it can be used to efficiently assimilate observational data (e.g., wave heights) in the interior of a model domain in order to update knowledge of the boundary conditions. The utility of this sort of assimilation is threefold. First, updated boundary conditions might be intrinsically useful. For instance, assimilation methods have been used to estimate nearshore bathymetry (Piotrowski and Dugan, 2002; Plant et al., 2008; Stockdon and Holman, 2000), which could be used independently of the network for navigation, safety, or validation of morphologic evolution models. Also, more highly resolved or accurate boundary conditions estimated using the Bayesian approach could be used to drive related, more detailed numerical models. Second, since the updated information in a Bayesian network can propagate to both boundary conditions and to variables within the model interior, observations can be used to optimally update all modeled variables simultaneously. The Bayesian network will make a prediction that appropriately weights the new information with respect to its prior predictions. Thus, if new data are very accurate, the Bayesian prediction will match all the data; whereas, if the data are very inaccurate or inconsistent, the prediction will be unaffected by the assimilated data. Third, the Bayesian network can be extended to assimilate variables that are not typically used as either input or output within detailed, numerical nearshore process models. For instance, observations of sandbar positions are available at some coastal locations (Lippmann and Holman, 1989; Plant et al., 1999; Ruessink et al., 2003b). Sandbars certainly indicate something about the bathymetry (it is shallow at the bar crest) and can have a direct impact on wave energy dissipation, but since the numerical depth of the bar is not known, sandbar position cannot be used directly as a numerical wave model input. In contrast, assimilation of sandbar position into the Bayesian network is straightforward. Other examples of observations not typically assimilated include surf zone width and the intensity of wave breaking.

In this paper, we investigate the inverse and assimilation capability of a Bayesian network developed from the 1-dimensional (1-D) process model described in detail in the companion paper. In Section 2 (this paper, Models), we briefly describe the previous work and introduce an extension that includes three additional variables: inner and outer sandbar positions and the normalized wave height (i.e., the local ratio of wave height to water depth, which is related to the intensity of wave breaking). These variables are selected because they can be estimated via remote sensing. In Section 3 (this paper, Applications), we test the ability of both the original and the extended Bayesian networks to estimate boundary conditions and assimilate data. As with the forward modeling (companion paper), we test both the ability to make accurate predictions and to estimate prediction uncertainty. Discussion of the implication of the analysis results and of sensitivity to input errors is presented in Section 4. Conclusions are presented in Section 5.

2. Models

A Bayesian network is based on multi-dimensional application of Bayes Rule:

$$p\left(F_i \mid O_j\right) = p\left(O_j \mid F_i\right) p(F_i) \, / \, p\left(O_j\right), \tag{1}$$

where the left side of Eq. (1) is the updated probability of a particular forecast, F_i, given a particular set of observations, O_j. The first term on the right-hand side of Eq. (1) is the inverse of the left side and is the likelihood of the observations if the forecast is known. The next term on the right side is the prior probability of each forecast. This is what is known about the problem before new data are available. The last term is a normalization factor to account for the total likelihood of the observations. Each of the terms on the right-hand side of Eq. (1) must be learned from model simulations or a calibration data set or both.

2.1. Nearshore model

In the companion paper, we have already described the wave model (Thornton and Guza, 1983). Here, it is treated as a general nonlinear model:

$$F_i(x_k) = \{H_k\}_i = funct.(\{h_0, h_1, \ldots, h_k, H_0, \alpha_0, T, \gamma, B\}_i), \tag{2}$$

where h is the water depth and H is the root mean square (rms) wave height. All variables with subscript k are spatially varying. Additional model inputs are the peak wave period (T), wave direction at the seaward boundary (α_0) and parameterized values for the critical wave breaking criteria (γ) and a wave energy dissipation efficiency term (B). All of the inputs can be considered random variables, since even the model parameters must be estimated from data (Apotsos et al., 2008; Ruessink et al., 2003a).

2.2. Bayesian network formulation

A Bayesian network was constructed to represent the wave model (Eq. (2)). The dimensionality of the problem was reduced by considering only three spatial locations (the offshore boundary and two interior locations). The original Bayesian network presented in Part I tracked the following forecast and observation values:

$$F_i = \{h_0, H_0, h_1, H_1, h_2, H_2, T, \alpha_0, \gamma, B\}_i$$

and (3a)

$$O_j = \left\{\hat{h}_0, \hat{H}_0, \hat{h}_1, \hat{H}_1, \hat{H}_2, \hat{h}_2, \hat{T}, \hat{\alpha}_0, \hat{\gamma}, \hat{B}\right\}_j.$$

The spatial locations are given by the subscripts (0 for the offshore boundary, 1 for the intermediate position, and 2 nearshore, Fig. 1).

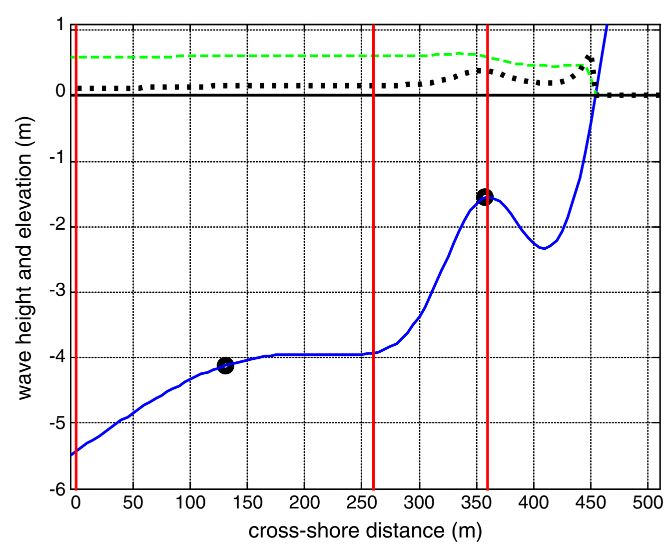

Fig. 1. Spatially varying data extracted at three locations (vertical lines) used to drive Bayesian network predictions. Data include simulated wave height (thin dashed green line), bathymetry (solid blue line), normalized wave height (thick dashed black line), and observed bar positions (large black dots).