Coastal Engineering 89 (2014) 53–62

Contents lists available at ScienceDirect

Coastal Engineering

journal homepage: www.elsevier.com/locate/coastaleng

A probabilistic method for constructing wave time-series at inshore locations using model scenarios

J.W. Long *, N.G. Plant, P.S. Dalyander, D.M. Thompson

USGS Coastal and Marine Geology Program, St. Petersburg Coastal and Marine Science Center, St. Petersburg, FL, USA

ARTICLE INFO

Article history:
Received 18 September 2013
Received in revised form 25 March 2014
Accepted 26 March 2014
Available online 4 May 2014

Keywords:
Coastal modeling
Waves
Wave prediction
Probabilistic models
Wave transformation

ABSTRACT

Continuous time-series of wave characteristics (height, period, and direction) are constructed using a base set of model scenarios and simple probabilistic methods. This approach utilizes an archive of computationally intensive, highly spatially resolved numerical wave model output to develop time-series of historical or future wave conditions without performing additional, continuous numerical simulations. The archive of model output contains wave simulations from a set of model scenarios derived from an offshore wave climatology. Time-series of wave height, period, direction, and associated uncertainties are constructed at locations included in the numerical model domain. The confidence limits are derived using statistical variability of oceanographic parameters contained in the wave model scenarios. The method was applied to a region in the northern Gulf of Mexico and assessed using wave observations at 12 m and 30 m water depths. Prediction skill for significant wave height is 0.58 and 0.67 at the 12 m and 30 m locations, respectively, with similar performance for wave period and direction. The skill of this simplified, probabilistic time-series construction method is comparable to existing large-scale, high-fidelity operational wave models but provides higher spatial resolution output at low computational expense. The constructed time-series can be developed to support a variety of applications including climate studies and other situations where a comprehensive survey of wave impacts on the coastal area is of interest.

1. Introduction

There is an increasing need for accurate, site-specific, and timely estimates of coastal wave properties that can be used to design marine infrastructure, perform coastal vulnerability assessments (e.g., Stockdon et al., 2012), evaluate potential sites for wave energy extraction (Defne et al., 2009; Reikard, 2009), and drive empirical (Stockdon et al., 2006; Yates et al., 2009) and process-based (e.g., XBeach, Roelvink et al., 2009) nearshore models. Wave properties for these applications are generally obtained from sparse buoy arrays (hindcast or nowcast) or a variety of process-based wave transformation models (hindcast, nowcast, and forecast). The models can range significantly in resolution, scale, and computational expense. Oftentimes highly spatially-resolved nearshore models are run deterministically by initializing with waves observed at buoy locations and allowing the model to transform the waves to the site of interest. However, these can be computationally expensive depending on the length of the time-series and number of wave conditions required, especially if statistical uncertainties are required (e.g., sensitivity testing). Alternately, operational wave forecasts, forced with predicted global and basin-scale wind fields, archive forecast output for future use in hindcast studies (e.g., WAVEWATCH-III®, Tolman (2008)). Despite the overall good skill of these forecasts, the resolution is typically O (3–7 km) which is insufficient to resolve some important shelf-scale features and nearshore wave transformation processes.

In order to improve the efficiency of wave prediction over operational or deterministic models, methods have been developed that exploit machine-learning techniques (e.g., Neural Networks, fuzzy logic, and Bayesian methods) to estimate wave characteristics at one location given information at another (e.g., Camus et al., 2011; Londhe, 2008; Londhe and Panchang, 2007; Plant and Holland, 2011a,b). While this is useful, for example, to fill data gaps at observational buoys, these techniques ("machine learning") do not provide information on the physical transformation of waves between the sites and require historical data at both locations to train the algorithms and determine the relationship between the wave fields at each site. The applicability of these methods is limited when information is desired at locations where no buoy has ever been deployed. One solution if observational data at the target site are unavailable is to use deterministic model runs to train the machine-learning models; however, the efficiency benefit of the machine-learning technique is then lost.

In a similar fashion, O'Reilly and Guza (1993) compared simple refraction and refraction–diffraction models and, from the model output, derived wave energy transformation coefficients to estimate coastal

* Corresponding author.
E-mail address: jwlong@usgs.gov (J.W. Long).

http://dx.doi.org/10.1016/j.coastaleng.2014.03.008
0378-3839/Published by Elsevier B.V.

wave properties based on offshore wave information. The coefficients are a function of frequency and direction and are region-specific. The method is computationally efficient but is only applicable for low-frequency swell in regions where offshore wave conditions are spatially homogeneous. Similar to the operational and deterministic methods, statistical confidence limits are not reported.

Here we present a probabilistic time-series construction technique that uses a process-based coastal and nearshore numerical wave model to transform deep water waves inshore. In contrast to the wave transformation or machine learning methods, this probabilistic method can construct a continuous wave time-series over a spatial domain of interest using a set of climatologically-based numerical simulations. The numerical model accounts for physical wave transformation processes, does not require algorithm training and does not require computationally expensive model runs. In addition, it is not limited to sites with available observations and may be applied to analyze possible future scenarios. We demonstrate the validity of the technique using time-series that span multiple years and locations and derive statistical uncertainty estimates based on historical distributions of the wave climate.

The probabilistic time-series construction method is described in Section 2. Results from two hindcasted probabilistic time-series constructions at locations in 12 m and 30 m water depths are presented in Section 3. In Section 4 we discuss limitations and sensitivity of the technique to some of our assumptions, and conclusions are synthesized in Section 5.

2. Methods

2.1. Derivation of wave scenarios

The probabilistic method relies on the establishment of a discrete set of climatologically-derived base model simulations, or wave model scenarios, representing the wave conditions within the domain under a variety of offshore conditions. Wave model scenarios were defined from a climatological binning of offshore wave observations. The data used for the climatological assessment were obtained from the National Data Buoy Center (NDBC) buoy 42040 from April 2010 to May 2012. This buoy is located in the Gulf of Mexico in approximately 165 m water depth (labeled 42040 in Fig. 1). The wave observations from this time period, which peaked at 5.1 m, were divided into 5 significant wave height (H_s) bins corresponding to 0 m < $H_s \leq$ 0.5 m, 0.5 m < $H_s \leq$ 1.0 m, 1.0 m < $H_s \leq$ 1.5 m, 1.5 m < $H_s \leq$ 2.0 m, and H_s > 2.0 m and 16 wave direction bins, each spanning 22.5°, from 0 to 360° (Fig. 2). The average of all the observed wave heights and directions that fall within each of the 80 climatological bins defines the targeted climatological conditions, and thus the offshore conditions for each wave model scenario.

To avoid the restriction of assuming homogeneity along the boundaries of our coastal model domain by applying only the targeted (average) significant wave height, peak period, and peak direction for each climatological bin, we used operational wave model forecast output along the boundaries of the domain. We performed a multivariate analysis to identify a best-match time in the buoy time-series when observed conditions most closely matched the average conditions for each climatological bin. The selected hour was required to come from a time period when the observed conditions met the targeted values for at least 6 h, rather than from a time period when conditions were rapidly transitioning from one sea state to another. Despite not being included as a constraint, the wave period and offshore winds for the selected hour representing each bin were also found to closely match bin-averaged values.

For each of the 80 model scenarios, spatially-varying bulk wave characteristics (height, period, direction) from the best-match times were extracted from archived NOAA WAVEWATCH-III® 4 (7.5 km) U.S. East Coast and Gulf of Mexico wave model results (Tolman, 2008) along all boundaries of our coastal domain (Fig. 1). This method described the spatially heterogeneous wave climate over a large region

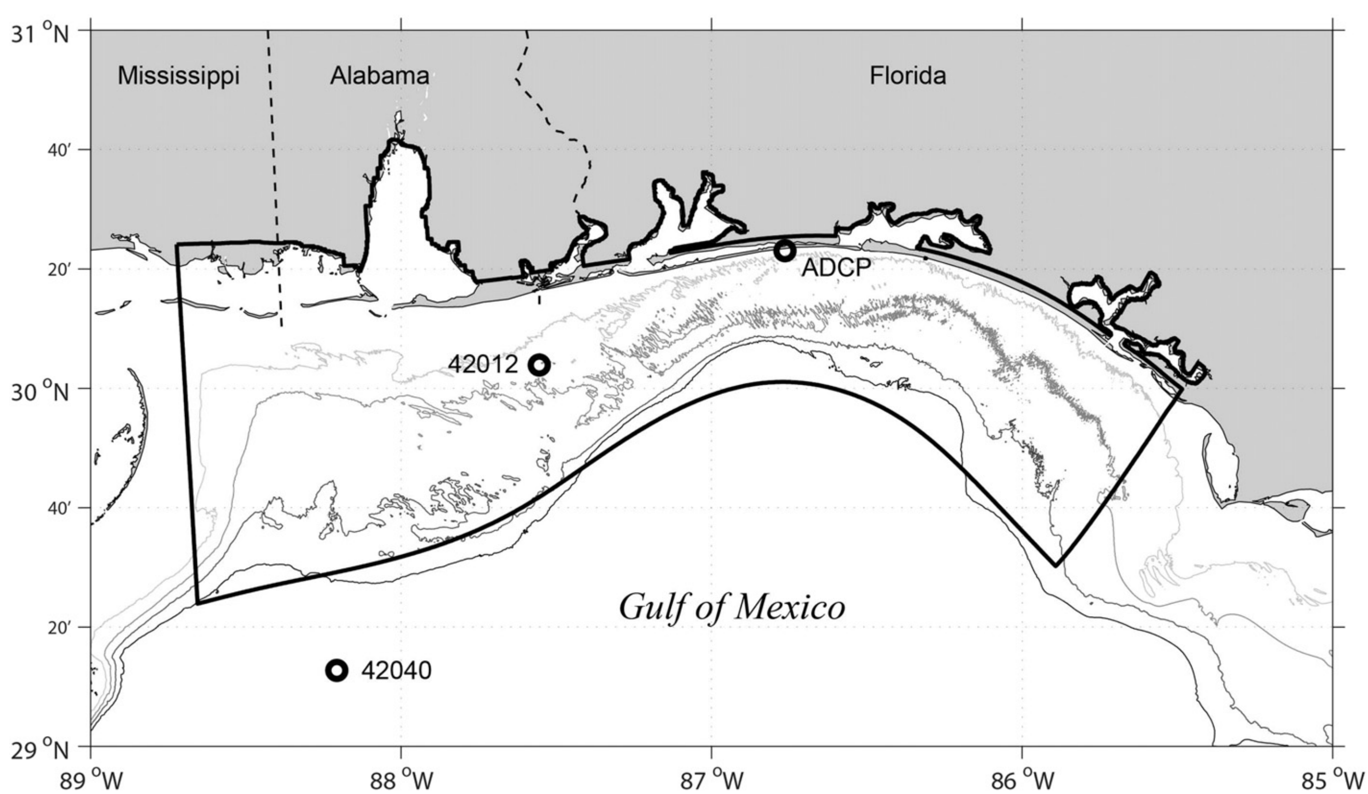

Fig. 1. Wave measurement locations (black circles) in the northern Gulf of Mexico. The coastal wave model domain is delineated by the solid black line and state boundaries are indicated by the dashed lines.