Coastal Engineering 77 (2013) 14–27

Contents lists available at SciVerse ScienceDirect

Coastal Engineering

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

How much data is enough? The importance of morphological sampling interval and duration for calibration of empirical shoreline models

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ARTICLE INFO

Article history:
Received 30 October 2012
Received in revised form 7 February 2013
Accepted 15 February 2013
Available online 19 March 2013

Keywords:
Empirical shoreline models
Model calibration
Beach monitoring programs
Coastal monitoring
Coastal change

ABSTRACT

The ability to robustly predict future shoreline position under the influence of changing waves and sea-level rise is a key challenge to scientists and engineers alike. While extrapolating a linear trend out in time is a common baseline approach, the recent development of a number of empirical shoreline models allows the prediction of storm and annual-scale variability as well. The largest constraint in applying these models is the availability of high quality, adequate duration data sets in order to calibrate model free parameters. This contribution outlines several such models and discusses the monitoring programs required to calibrate and hindcast shoreline change from 1 to 10 years at two distinct beach types: a storm-dominated site and the second exhibiting a large seasonal variability. The seasonally-dominated site required longer data sets but was less sensitive to sampling interval, while the storm-dominated site converged on shorter, more frequently sampled data sets. In general, calibration based on a single year of observed shorelines resulted in a large range of model skill and was not considered robust. Monitoring programs of at least two years, with shorelines sampled at $dt \leq 30$ days were sufficient to determine initial estimates of calibration coefficients and hindcast short-term (1–5 years) shoreline variability. In the presence of unresolved model processes and noise, hindcasting longer (5+ years) data sets required longer (5+ years) calibration data sets, particularly when sampling intervals exceeded 60 days.

1. Introduction

Future uncertainty surrounding changing wave climates and sea-level rise requires that coastal scientists and engineers understand and can predict how this will impact future shoreline position. Knowledge of individual storm-scale response and recovery, seasonal variability, and annual to decadal-scale trends are required to assess the vulnerability of sandy coastlines to these drivers. Long-term observational data sets are typically limited in both their temporal and spatial resolution, ranging from daily single point measurements of sand thickness (Barnard et al., 2012) or a single cross-shore beach profile (Kuriyama, 2012), biweekly to monthly cross-shore profiles over a short spatial range (Birkemeier et al., 1999; Harley et al., 2011; Short and Trembanis, 2004), to annual profiles extending over a large stretch of coastline (Wijnberg and Terwindt, 1995). These observational programs, along with many other short-term programs have been used to identify everything from beach response to tides (Eliot and Clarke, 1988) and individual storms, to seasonal-scale (e.g. Aubrey, 1979; Hansen and Barnard, 2010; Inman, 1953; Shepard, 1950), as well as annual (Clarke and Eliot, 1988), and decadal-scale (Short and Trembanis, 2004) variability and change.

Along non-engineered, exposed sandy coastlines, changes in wave energy arriving at the coast, rather than changes in sea level, are presently expected to be the dominant process impacting shoreline change in the coming decades (e.g. Brunel and Sabatier, 2009; Ruggiero, 2008, 2013). Both cross-shore and alongshore sediment transport processes drive changes in shoreline position, however, alongshore processes generally act over much longer time frames, and along many exposed coastlines do not dominate the annual shoreline variability (e.g. Clarke and Eliot, 1988; Davidson and Turner, 2009; Davidson et al., 2010; Hansen and Barnard, 2010; Yates et al., 2009). A number of equilibrium-based empirical shoreline models have recently been developed that are capable of capturing the seasonal to multi-year variability of shoreline behavior at cross-shore dominated study sites (e.g. Davidson and Turner, 2009; Davidson et al., 2010, 2013; Frazer et al., 2009; Miller and Dean, 2004a; Yates et al., 2009). These models all assume that shoreline variability due to gradients in alongshore transport is small compared to the variability associated with cross-shore processes and as such is acknowledged as an unresolved process (noise) and/or can be reasonably approximated by a linear term over annual to decadal scale shoreline modeling. When gradients in alongshore transport are significant, vary temporally, or cannot be parameterized by a linear trend term, these types of models are no longer valid.

The empirical nature of these models requires high-quality observational data sets to calibrate model free parameters. To illustrate,

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0378-3839/$ – see front matter
http://dx.doi.org/10.1016/j.coastaleng.2013.02.009

Fig. 1 provides two field examples where observed shorelines were used to calibrate an empirical shoreline model and then results were used to hindcast future shoreline position. The top example shows model calibration to three years of fortnightly (dt = 14 days) sampled shorelines at a storm-dominated beach ($R^2 = 0.46$) with a further one year of model hindcast ($R^2 = 0.74$). The bottom example shows model calibration to two years of 60-day sampled shorelines at a seasonally-dominated site ($R^2 = 0.69$) and a three-year hindcast ($R^2 = 0.49$). Optimum model calibration varied in both length, prediction horizon, and sample spacing between these two examples. There is presently a lack of general guidance as to how much data and what sampling interval is required to constrain these model free parameters and hence, define their prediction horizon. In addition, are sampling requirements beach-type dependent? Is there an optimum length of calibration data required and does model skill deteriorate if too long or too short a data set is used for calibration?

This contribution examines the sensitivity of an empirical shoreline model driven primarily by cross-shore processes to shoreline sampling duration and frequency to determine the minimum data collection required to predict shoreline position between 1 and 10 years in the future. The results presented here are consistent with, and extend on previous findings based on similar models outlined in Section 2 and are therefore offered as generic guidelines. This is followed by a brief description of the present model and the calibration methodology in Section 3. A summary of the data sets: both synthetic and field is provided in Section 4. Results are presented in Section 5 and discussed with recommendations in Section 6.

2. Background

Here we summarize the works of several research teams who have made recent and significant contributions in the field of equilibrium shoreline models. Miller and Dean (2004a) presented a model that relates the rate of change of shoreline position to a rate parameter, k, and the disequilibrium between a time-varying equilibrium shoreline position and the current shoreline position (see Table 1). The time-varying equilibrium follows a Bruun-type approach and is a function of the instantaneous total water-level and waves (Dean, 1991). Miller and Dean (2004a) calibrated and tested their model at 10 USA sites using shoreline data derived from beach profiles and aerial photographs spanning monitoring periods of 2–40 years with sampling intervals between biweekly to beyond annually. They used an error minimizing technique to solve for their three free parameters. Hindcasting showed that their model was most successful at predicting medium-term (seasonal) changes and that sites with a larger degree of longshore uniformity resulted in better model performance. Lowest normalized mean square errors (NMSE, Eq. (5), an estimator of the error variance compared to the variance of the data) were found at Wildwood, New Jersey, based on nine years of approximately annual surveys (NMSE = 0.301), and Long Beach, Washington, based on four years of quarterly surveys (NMSE = 0.33). Despite having 22 years of monthly profile data for Duck, NC, this site had the highest NMSE (0.95) and low model skill was attributed to the high alongshore variability in the shoreline. Additional work by Miller and Dean (2004b) utilized 3 additional Australian data sets, including a 3-year data set from the Gold

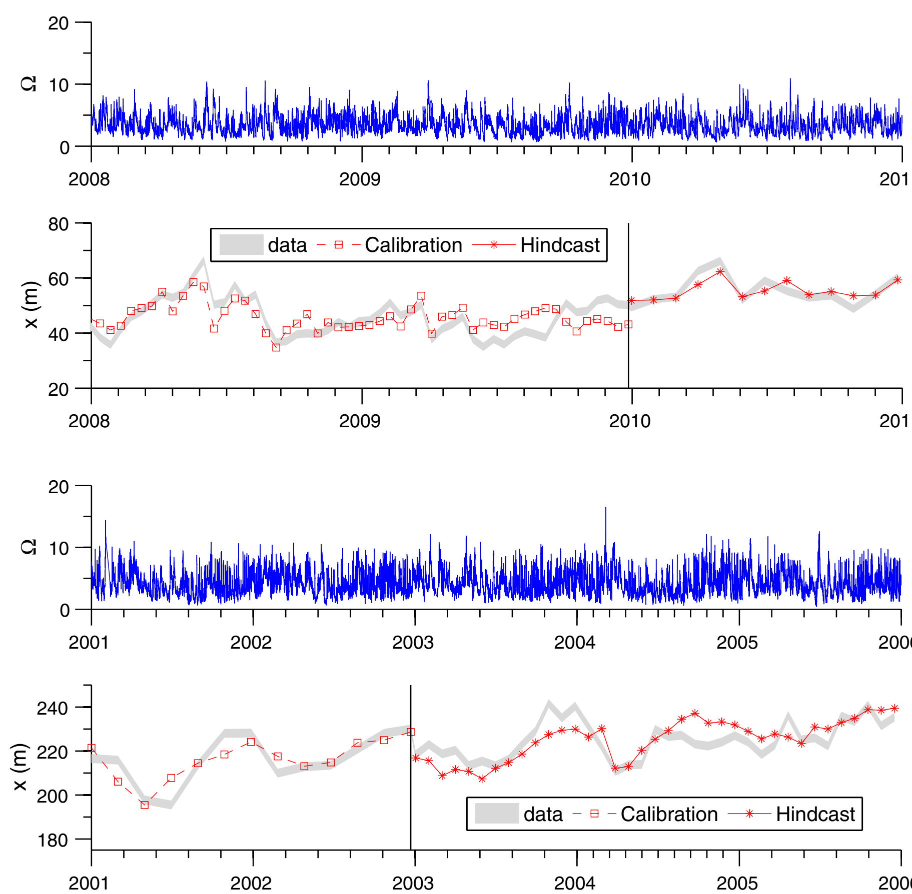

Fig. 1. An example of the best calibration and hindcast results for the two field beach types explored here. (Top 2 panels): NB2600. Calibration statistics: $R^2 = 0.46$, NMSE = 0.54, sampling frequency, $dt = 14$ days. Hindcast statistics: $R^2 = 0.74$, NMSE = 0.32. (Bottom 2 panels) GCn1000. Calibration statistics: $R^2 = 0.69$, NMSE = 0.32, sampling frequency, $dt = 60$ days. Hindcast statistics: $R^2 = 0.49$, NMSE = 0.67.