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A simple new shoreline change model

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Abstract

A simple new shoreline change model has been developed and calibrated/evaluated with several sets of high quality field data. The model is based upon the general observation that the shoreline tends to approach an equilibrium position exponentially with time when subjected to constant forcing. The model represents the shoreline response to cross-shore processes only and is extremely efficient, requiring only readily obtainable wave and water-level data as input. Shoreline changes are forced by changes in the local water surface elevation due to a combination of local tide, storm surge and wave-induced setup. The model contains three adjustable parameters, representing a baseline condition from which equilibrium shoreline displacements are calculated, and two rate constants, all of which are evaluated by minimizing the error between model hindcasts and several historical shoreline data sets. Several possible forms for the rate parameters, incorporating local wave and sediment properties, were considered and evaluated. At most sites, the model has proven successful in predicting large-scale shoreline response to local water level and wave forcing. The combination of model accuracy and efficiency, along with the minimal data required to drive the model, make it a potentially useful tool in many coastal engineering applications. As more high-quality shoreline, wave and water-level data sets become available, significant improvements can be made in the determination of the rate parameter governing the time scale of the beach response.

Keywords: Shoreline change; Shoreline model; Profile model; Shoreline variability; Cross-shore process

1. Introduction

Coastal engineers and scientists routinely address a wide variety of coastal problems. How will proposed structures affect adjacent shorelines? How long will a beach nourishment project last? What will be the effects of altering an existing inlet? Despite our ability to answer a number of challenging questions such as these, we are still unable to adequately answer a much more basic question. Where will the shoreline be tomorrow? Next week? Next year? In a decade? The reasons for our inability to address this question in a satisfactory manner are numerous. The many factors that make beaches and the entire nearshore environment so fascinating to study make them extremely difficult to model accurately. Beaches are extraordinarily complex, dynamic systems, experiencing changes on a variety of different temporal and spatial scales. These changes range from small-scale fluctuations due to the formation of beach cusps to large-scale changes caused by longshore migrating sand waves, episodic storm events or seasonal weather patterns. The

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paucity of frequent, high-quality surveys encompassing the entire nearshore system only makes the task of describing and predicting profile changes that much more challenging. Despite the significant strides made in our understanding of nearshore processes in the last decade, describing shoreline changes over the full range of relevant temporal and spatial scales remains a daunting task.

The monumental task of modeling the shoreline over the entire spectrum of temporal and spatial scales can be simplified somewhat if only a subset of relevant scales is considered. Fortunately, space and time scales are related, with large-scale shoreline changes generally occurring with longer time scales. The so-called engineering time scale is arguably the most relevant time scale, and hence the focus of this paper. The engineering time scale refers to the range of shoreline changes expected to impact a structure during its lifetime. This range generally encompasses everything from storm-induced changes with time scales on the order of hours, up to long-term changes with decadal time scales. Due to our present inability to predict long-term changes adequately using a generally applicable shoreline change model, many developers, engineers and coastal managers continue to rely upon outdated, rudimentary extrapolations of some best-fit trend line to predict future shoreline changes. A more complete method for predicting future shoreline migration must account for shoreline changes on a variety of time scales including both the seasonal and storm time scales. Although periodic trends such as seasonal fluctuations or El Niño related phenomena are much easier to predict than storm-induced changes, both have significant impacts on the shoreline and must be included in any complete model. The aperiodic nature of storm events, and the uncertainty of future weather conditions, argues for the use of some statistical simulation procedure such as a Monte Carlo technique. Utilizing such a procedure, the probabilities associated with various magnitudes of shoreline change may be calculated based upon the statistical characteristics of the forcing parameters.

The prediction of shoreline migration can be simplified even further by separating the changes due to longshore processes and largely responsible for long-term changes from those caused by cross-shore processes and tending to operate on much shorter time scales. A notable exception to this generalization is the shoreline change related to long-term sea-level variability which results in a readjustment of the profile to the new water levels and is a cross-shore response. This separation procedure is commonly applied and leads to two broad categories of morphological models: coastal area or longshore models and profile or cross-shore models. Although several highly detailed process-based morphological models exist, these models tend to be computationally intensive and their accuracy near the shoreline over a broad spectrum of relevant time scales has not been demonstrated. Additionally, the complexity and computational costs involved in applying these detailed models to the nearshore region, over long time scales, makes them inefficient at the present time for long-term shoreline studies.

The objective of this paper is to present a new shoreline change model capable of reproducing the shoreline response to cross-shore forcing over a variety of temporal scales. Simplicity and efficiency, while maintaining a sufficient level of accuracy thus ensuring the widest possible range of applicability, were primary considerations. Historical shoreline data from the locations depicted in Fig. 1 have been used to calibrate and evaluate the model. The temporal density of the available shoreline data allows for the skill of the model to be evaluated over a variety of time scales ranging from biweekly to multidecadal. The geographical diversity of the data sets provides an interesting platform for examining the natural variability in the nearshore system and for evaluating the model over a wide range of beach conditions. As more data become available, additional sites will be incorporated into the analysis in order to test the robustness of the model.

The efficiency of the model makes it particularly useful for long-term studies ranging from the prediction of seasonal shoreline changes to the prediction of decadal shoreline migration patterns for coastal management applications. The simplicity of the proposed model makes it ideal for representing the shoreline response to cross-shore processes in a simple one-line model, similar to the approach of Hanson and Larson (1998). A cross-shore model requiring minimal input would be an improvement over the parameterizations used to represent cross-shore processes in their original model. Given the modest amount of data required to drive the model, and the general availability of this data, the model could also be applied in a real-time

Fig. 1. Locations of shoreline data used to calibrate and validate the proposed model.

sense to provide first-approximation predictions of the erosive potential of approaching storms.

2. Background

Although many significant advancements have been made in the science of hydrodynamics and sediment transport in the past decade, these advancements have yet to yield accurate shoreline change models applicable over the full spectrum of time scales of engineering relevance (storms, seasonal and decadal). The complexity involved in modeling the extremely dynamic nearshore region has led to the development of a number of different approaches. Roelvink and Broker (1993) and van Rijn et al. (2003) provide valuable reviews and intercomparisons of many of the state-of-the-art European cross-shore profile models. Roelvink and Broker (1993) classified the different modeling techniques into four categories: descriptive models (e.g., Wright and Short, 1984), equilibrium profile models (e.g., Swart, 1975), empirical profile evolution models (e.g., Larson and Kraus, 1989) and process-based models (e.g., Dally and Dean, 1984). Davies et al. (2002) further divided the process-based models into two categories: research models, containing full, detailed descriptions of the governing physics, and practical models that simplify the governing processes to varying degrees and which are more empirical in nature. A more general classification system used by Dean and Dalrymple (2002) combines the equilibrium profile models and empirical profile evolution models under the more broad classification of "closed loop" models, where the term "closed loop" refers to the fact that the equilibrium, or final profile configuration, is predescribed. The classification systems described above represent just a few of the more popular methods used to categorize cross-shore profile models. As hybrid models that combine successful techniques from several of the classical categories become more popular, the lines separating the various categories are becoming blurred.

Most of the aforementioned model comparisons have generally confirmed that the current state-of-the-art process-based models are much more successful at modeling the more two-dimensional offshore region of the profile than the dynamic and highly three-dimensional nearshore region including the shoreline. This is unfortunate because while bar topography and other subaqueous features are of extreme interest to scientists and researchers, engineers, developers and the general public are often ultimately concerned with the shoreline location. In their comparison of five of the most advanced shoreline evolution models, van

Rijn et al. (2003) found that using current state-of-the-art modeling techniques, accurate predictions of bed-level changes in the inner surfzone and beach zone were not feasible with these models. Far from being a criticism of existing models, this is instead a testament to the extreme difficulty in representing all of the complex physical interactions within the surfzone, which result in the highly three-dimensional nearshore morphology. Plant et al. (1999) and Miller and Dean (2003) examined the longshore uniformity at Duck, NC, and found a general increase in uniformity with increasing distance offshore. These results imply that morphology becomes increasingly two-dimensional and thus potentially easier to model in the offshore region of the profile. Although process-based models ultimately hold the most promise for predicting and understanding the processes driving shoreline changes, a variety of factors currently limit their usefulness for many long-term engineering studies. In many cases, the vast data requirements required for calibration, combined with questionable accuracy near the shoreline, do not justify their computational cost. Until more practical process-based models are developed, a simple new shoreline change model is proposed for use by engineers and scientists that has the potential to provide reasonably accurate shoreline evolution predictions at a fraction of the computational cost.

3. Model development

3.1. Theoretical development

Traditionally, models have been grouped into one of three categories, empirical, analytical or numerical based upon the character and complexity of the equations involved and the solution technique. The new shoreline change model presented here utilizes a combination of these traditional approaches. An analytical equation suggested by empirical evidence is solved numerically and is then calibrated using historical shoreline data. Laboratory investigations by Swart (1974), along with previous numerical simulations by Kriebel and Dean (1985) and Larson and Kraus (1989), have suggested that a shoreline approaches an equilibrium form for steady-state conditions at an approximately exponential rate. The governing differential equation for such a process is given by:

$$\frac{\mathrm{d}y(t)}{\mathrm{d}t} = k(y_{\mathrm{eq}}(t) - y(t)) \tag{1}$$

where $y(t)$ is the shoreline position at time t, $y_{\mathrm{eq}}(t)$ is the equilibrium shoreline position determined by the forcing at time t and k is a constant governing the rate at which the shoreline approaches equilibrium. Eq. (1) represents a classical equilibrium or linear relaxation equation and has many engineering applications. Wright et al. (1985) use an equation of this form to represent the rate at which a beach changes its state, and equations of this form have been used to describe bar evolution (Plant et al., 1999) and beach slope change (Madsen and Plant, 2001) as well.

Kriebel and Dean (1993) solved Eq. (1) analytically in terms of a convolution integral.

$$y(t) = k\int_0^t y_{\mathrm{eq}}(\tau)e^{-k(t-\tau)}\mathrm{d}\tau + y(0) \tag{2}$$

where τ is a time lag and $y(0)$ is the initial shoreline position. The convolution integral solution includes the effects of beach memory and results in a solution that is both damped and lagged with respect to the maximum or equilibrium shoreline response. The analytical solution is somewhat limited in application, however, because Eqs. (1) and (2) can only be solved for a limited number of idealized forcing functions $y_{\mathrm{eq}}(t)$. Although a numerical filter could be designed and applied to the above equations in order to potentially extend the analytical solution, direct numerical techniques, offering the promise of more robust solutions, are applied here.

Several of the limitations of the analytical solution are avoided by utilizing a numerical finite difference approach. One of the advantages of utilizing a numerical approach is that the restrictions placed on the form of the forcing function $y_{\mathrm{eq}}(t)$ are removed, allowing more realistic and complex forms of $y_{\mathrm{eq}}(t)$ to be represented. Using finite differences, Eq. (1) can be rewritten as:

$$y^{n+1} = \frac{y^n + A[(y_{\mathrm{eq}}^{n+1} + y_{\mathrm{eq}}^n) - y^n]}{1+A}, \qquad A = \frac{k\Delta t}{2} \tag{3}$$

where an unconditionally stable, semiimplicit Crank–Nicholson scheme is used, which provides order two accuracy and computational efficiency. The oscillatory nature of the forcing function $y_{eq}(t)$ limits the buildup of numerical error, as errors tend to cancel rather than perpetually increase. The maximum response or equilibrium shoreline position, y_{eq}, is defined as that which would be attained if the forcing conditions were held constant indefinitely and may be calculated from either observed or simulated data. In reality, the equilibrium shoreline is a dynamic quantity, changing significantly with time scales on the order of hours; however, over a single time step, the forcing is assumed to remain constant. As with the analytical solution, the actual shoreline response will be lagged and damped with respect to the equilibrium shoreline. The particular time step used in model simulations varies with the temporal density of the input data but is generally on the order of several hours. In all cases, the resolution of the forcing data is sufficient to capture the shortest time scales intended to be reproduced by the model, which are associated with severe storms.

Previous numerical and empirical studies have indicated that the most significant shoreline changes occur in response to increases in the local water surface elevation in combination with large waves. Fig. 2 illustrates the shoreline response to an increase in local water level due to a combination of storm surge, S, and wave-induced setup, $\bar{\eta}$. Utilizing equilibrium beach profile theory, and a Bruun-type conservation of volume argument, the equilibrium shoreline change, $\Delta y_{eq}(t)$ due to a combination of wave-induced setup, and storm surge can be shown to be approximately (Dean, 1991):

$$\Delta y_{eq}(t) = -W^*(t)\left(\frac{0.068H_b(t) + S}{B + 1.28H_b(t)}\right) \tag{4}$$

where $H_b(t)$ is the breaking wave height, B is the berm height, and $W^*(t)$ is the width of the active surfzone, which in this case is defined out to the break point [$W^*=(h_b/A)^{1.5}$, where A is the so-called "profile scale parameter"; Moore, 1982; Dean, 1991]. The wave height and breaking index used in the derivation of Eq. (4) assumes constant or average wave conditions. An alternate form of Eq. (4) may also be derived for significant wave conditions where the coefficients in the numerator and denominator are replaced by 0.106 and 2.0, respectively. Here, significant wave conditions refer to a spectrally based wave height obtained over the interval between computations, which varies depending upon the data set, but is generally on the order of 1–3 h.

The equilibrium shoreline change given by Eq. (4) is then converted to an equilibrium shoreline position according to:

$$y_{eq}(t) = \Delta y_o + \Delta y_{eq}(t) \tag{5}$$

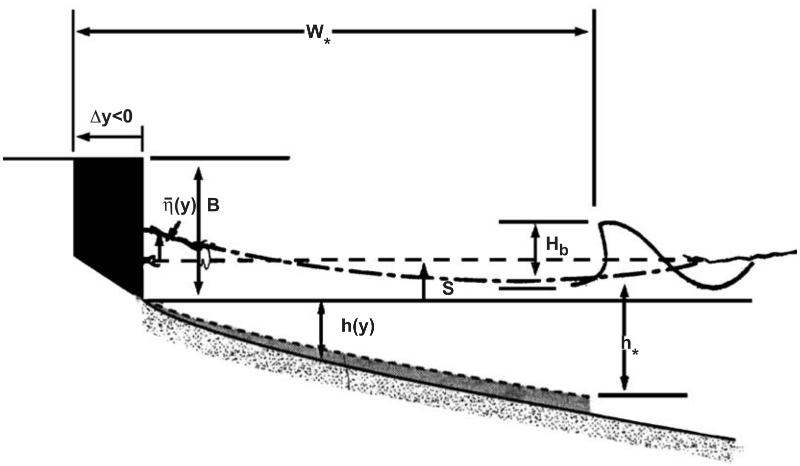

Fig. 2. Shoreline change resulting from an increase in water level due to a combination of storm surge and wave-induced setup (from Dean and Dalrymple, 2002).

where Δy_o is an empirical constant determined (along with the rate constants) by minimizing the normalized mean square error (NMSE) between shoreline measurements and model hindcasts. At this point, further discussion of the quantity Δy_o is warranted. The quantity $\Delta y_{eq}(t)$ calculated from Eq. (4) gives the shoreline change from a stable or baseline condition. In order to convert this time series of equilibrium shoreline change into a time series of equilibrium shoreline displacement, this baseline or stable condition must be identified. If the assumption is made a priori that the baseline condition corresponds to the average measured shoreline, Δy_o will be approximately zero (because the data are detrended). This assumption is not necessarily correct, however, as the baseline condition for $y_{eq}(t)$ may not correspond to an average measured shoreline position (particularly if this average is based on a limited number of points). It is for this reason that Δy_o is taken as a free parameter and is determined empirically.

In order to account for long-term trends in the shoreline data (which are assumed to be due to longshore processes), two options were considered. Initially, an extra term, $m(t-t_0)$, was added to Eq. (5), where m is the long-term trend determined from a linear least squares analysis of the historical shoreline data and the $t-t_0$ term accounted for the elapsed time during a simulation. The implication of this method is that the long-term trend exhibited by the actual shoreline is entirely reflective and identical to the long-term trend in the underlying equilibrium shoreline position. The second, more efficient option which is employed here, is simply to remove a linear long-term trend from the historical shoreline data using a linear least squares procedure, prior to applying the model. Long-term trends in the data range from a maximum of nearly +10 m/yr at Wildwood, NJ to a minimum of −6 m/yr at Torrey Pines, CA (after the adjustment described in Section 4). All long-term trends removed are assumed to be linear, and the validity of this assumption is a strong function of the length of the data set, survey frequency and of the likelihood that some of the older surveys were performed immediately following storms. It is recognized that a portion of the removed long-term trend may actually result from cross-shore related processes such as sea-level rise (which can be represented by the model); however, in general, the assumption of long-term trends dominated by longshore processes, and thus removed, appears justified. It is the intent to eventually apply the shoreline model in conjunction with a one-line model so that the impact of both the longshore and cross-shore processes can be studied in more detail.

3.2. Rate parameter dependence

The rate parameter introduced earlier, k, accounts for the rate at which the shoreline approaches equilibrium. Several possibilities exist and were investigated for the form of this parameter. The simplest representation is to assume that it is a locally determined constant, k_α. Recognizing the significant difference between the rates of erosion and accretion, the constant is assumed to have distinct values for each process. It is expected that the erosion rate constant, k_e, will be significantly larger than the accretion rate constant, k_a, as the erosion process generally occurs much more rapidly. Although convenient, this representation is perhaps overly simplified, as it is logical to consider that the rate parameter depends in some manner on the local conditions. One logical choice is to assume that the rate at which the shoreline changes is proportional to some measure of the wave energy. Plant et al. (1999) suggested the following form for their parameter, $\alpha(t)$ [equivalent to our $k(t)$], which governs the rate of bar response:

$$\alpha(t) = \alpha_1 H(t)^p \tag{6}$$

where $H(t)$ is a representative wave height and p is an exponent to be determined empirically. A similar dependence is considered here where $k(t)$ is assumed to be a time-dependent function of the breaking wave height raised to either the second or third power. The rate coefficient k_α (α_1 using Plant's notation) is again assumed to have different values for erosion and accretion, although the inclusion of local factors is expected to reduce the spread in the locally determined coefficients, k_a and k_e, between sites. One of the major disadvantages of this proposed relationship, however, is that it contains no dependency on either sediment size or wave period. In addition, in order for Eq. (1) to remain dimensionally consistent, the rate coefficient must take on the increasingly complex units of time^{-1} length^{-p}. Another logical form of the rate parameter, which avoids some of the disadvantages of the previous formulation, is:

$$k(t) = k_\alpha \Omega(t)$$

$$\Omega(t) = \frac{H_b(t)}{w_s T(t)} \quad \text{(7a and b)}$$

where $\Omega(t)$ is the nondimensional fall velocity parameter, w_s is the sediment fall velocity and $T(t)$ is the wave period associated with $H_b(t)$. Many previous studies have documented the utility of the fall velocity parameter in determining the direction of sediment transport and the resulting profile evolution (Dean, 1973; Wright et al., 1985; Kraus et al., 1991). The dependence suggested by Eq. (7) is appealing in that, it combines both wave and sediment properties and retains the original units of inverse time for the rate coefficient.

The parameterizations given in Eqs. (6) and (7) represent only a small subset of the possible parameterizations for $k(t)$. Valid physical arguments exist for a relationship between $k(t)$ and many other dimensional (H_b/T, H_b^4) and nondimensional (Froude number, surf similarity parameter) quantities as well. It is also entirely possible that a single parameterization will not be appropriate for both erosion and accretion. Although other possibilities have been explored, the four options presented in this paper:

- k constant,
- k proportional to H_b^2,
- k proportional to H_b^3 and
- k proportional to Ω,

represent perhaps the most obvious and useful parameterizations. It is not the intent of the present work to present an exhaustive list of potential parameterizations for $k(t)$ but rather to examine a limited number of possibilities in the context of the model and to use the information gained to help determine whether additional research into the appropriate form of the rate parameter is needed/warranted.

3.3. Model performance evaluation

The completely specified model contains three empirical coefficients, two rate constants/coefficients, k_a and k_e, and the equilibrium shoreline displacement, Δy_o. These constants are determined by comparing model hindcasts with historical shoreline data, at a number of sites. An error minimization technique was used to determine the appropriate constants, utilizing the following definition for the normalized mean square error (NMSE):

$$\text{NMSE} = \frac{\sum_i (y_{p_i} - y_{m_i})^2}{\sum_i y_{m_i}^2} \quad (8)$$

where y_p are model hindcasts and y_m are measured shorelines. A perfect model is characterized by a NMSE of 0 because all of the predictions exactly match the measured values. Although Eq. (8) is unbounded at its upper limit, errors on the order of one are indicative of model predictions with mean square deviations from the measured data approximately equal to the variance of the measured data. In general, the NMSE is an extremely effective measure of model performance; however, because the difference term in the numerator is squared, it has the unfortunate property of being oversensitive to large deviations. The presence of only a few outliers can significantly affect the NMSE and result in high errors for an otherwise good model.

An alternate measure of model skill, which has been used with increasing regularity, is the Brier Skill Score (BSS),

$$\text{BSS} = 1 - \frac{\sum (y_p - y_m)^2}{\sum (y_b - y_m)^2} \quad (9)$$

where y_b is a somewhat arbitrary baseline condition. In this case, if y_b is selected to correspond to the shoreline extrapolated from the long-term trend, the BSS simply reduces to the complement of the NMSE defined previously. The NMSE is used throughout the remainder of this paper; however, the interested reader is referred to Sutherland and Soulsby (2003) for a more in depth discussion of the BSS.

A significant limitation of both the NMSE and the BSS is that neither directly evaluates the ability of the model to predict the correct direction of shoreline change. By squaring the difference term in the numerator of the NMSE, the directional information is lost. Therefore, smaller errors can result from incorrectly predicting the direction of shoreline migration (if $y_{\mathrm{p}} - y_{\mathrm{m}}$ is small) than from correctly predicting the direction of migration, but severely overpredicting the magnitude. In order to evaluate model skill in predicting the appropriate direction of shoreline change, a categorical assessment procedure was applied. Shoreline changes were divided into three general categories: accretion, erosion and no change (or stable). A shoreline is defined as stable if the change in shoreline position between two successive surveys is less than 5% of the maximum range in measured shoreline position over the entire data set. This relative definition provides a useful sliding scale, whereby energetic coastlines may undergo more significant changes and still be considered stable. The ability of the model to predict the direction of shoreline change was quantified by comparing the number of measured events of each type to the number predicted correctly. For example, if 10 erosional events occurred and the model predicted 7 of those correctly, the model is said to be 70% accurate in predicting erosional events.

Finally, a somewhat subjective Model Performance Index (MPI) was defined which incorporates both of the aforementioned measures of model skill, while also taking into consideration some of the subtleties of the data sets and error definitions which may affect the evaluation of the model. As discussed previously, the NMSE assigns excessive weight to large deviations from the measured data. Consequently, although overall the model may perform well, one large deviation can result in errors that are somewhat misleading and not representative of the true model performance. The MPI takes into account many factors including the longshore uniformity of the subject shoreline, the minimum and average NMSE and a subjective analysis of the model's overall performance. Because the simple model is not intended to predict small-scale spatial fluctuations, the longshore uniformity provides a useful measure of expected model performance where uniform shorelines are expected to be modeled more accurately. Although the model should not be judged based on the NMSE alone, it does provide a quantitative measure of the model performance and must be included in any evaluation of its overall performance. The results are also examined subjectively, however, to determine whether the calculated error is in fact a good estimator of the overall model performance at a given location or whether the error calculation is biased by a single large deviation from an observed value. The quality of both the input data, as well as the shoreline data, with which the model results are compared, also plays an important role in the development of the MPI. Sites with excellent data are expected to be modeled more accurately than sites where either the forcing or the shoreline data are of lesser quality. The MPI ranges from 1 to 5, where the ratings correspond to the following: 1, bad; 2, poor; 3, reasonable; 4, good; 5, excellent.

4. Site selection

4.1. Field site description

In order to test the robustness of the model, 10 different sites representing a variety of different coastal environments were used to calibrate and evaluate the model. These sites are depicted in Fig. 1 and include both beaches typical of the high-energy, rocky headland-dominated Pacific coastline, as well as those representative of the low-lying barrier island topography found along much of the Atlantic coast. Although there may appear to be a bias towards East Coast data, this is purely a result of data availability, and as additional data sets are located, they will be added to the study. Nearly all of the shoreline data were obtained from direct beach measurements (either profiles or beach width surveys), with the exception of some of the Florida data which were obtained from aerial photographs. In an effort to minimize anthropogenic effects, only sites located a sufficient distance from natural or man-made structures including, jetties, groins, headlands, piers, and beach nourishment were selected. The data from Duck, NC are an exceptional case and are examined in part to demonstrate the ineffectiveness of the model, on shorelines with significant longshore nonuniformities such as those induced by the U.S. Army Corps of Engineers Field Research Facility (FRF) pier. The character of the historical data sets is such that the model performance can be evaluated over a number of different time scales. In general, the temporal resolution of the historical shoreline data varied from monthly surveys at Torrey Pines and Duck, to quarterly surveys in Washington, to more sporadic shoreline measurements available every several years in Florida. Brief descriptions of each site are provided below in conjunction with Table 1 which summarizes some of the important site information.

The Washington State shoreline data were collected as a part of the Washington State Coastal Erosion Study which is being conducted jointly by the United States Geological Survey and the Washington Department of Ecology. Data from the Long Beach subcell (part of the larger Columbia River littoral cell), which stretches approximately 45 km between Willapa Bay and the Columbia River, were used in this analysis. Profile data have been collected on a quarterly basis at the site since the fall of 1998, with biannual data available beginning in the summer of 1997. Data summaries including sediment size, beach slope and the location of the 2- and 3-m depth contours are available on the Washington Department of Ecology website. The Washington coastline is a typical high-energy coastline where significant wave heights (measured in 228 m of water) average 2.3 m and increase up to 3.3 m during the winter months. The tide range at the site is semi-diurnal and averages 2.7 m. Shoreline changes at the site are typically related to storms, a strong seasonal oscillation, El Niño/La Niña weather patterns, and long-term events including geologically frequent subduction zone earthquakes.

Shoreline data for Torrey Pines were extracted from 2 years of profile data reported by Nordstrom and Inman (1975). The data represent one of the first sets of complete profile data and extend past the so-called depth of closure to a depth of approximately 18 m. Surveys were conducted on a monthly basis, along three shore-perpendicular transects between June 1972 and April 1974. Nearshore wave conditions along this section of the California coast vary significantly due to the extremely irregular offshore bathymetry including numerous submarine canyons; however, a mean annual significant wave height of approximately 1.1 m was reported by Scripps buoy 101 in 549 m of water over the period 2001–2003. The wave climate exhibits a distinct periodicity similar to the Washington coast; however, the range of variability (0.8–1.3 m) is reduced considerably. The semidiurnal tide range averages 1.6 m, and like the Washington site, exhibits a large diurnal inequality. Shoreline changes occur over a variety of time scales at the site; however, the short duration of the data set limits the analysis to changes with periods of 2 years or less.

Table 1
Site information and data sources

Site	Latitude/ Longitude	Shoreline orientation[a]	d_{50} (nm)	Wave data source	NOAA tide gauge ID no.	Shoreline data type
New York						
East Hampton	40.9°/72.2°	151°	0.375	Buoy-44025 WISII-79	8531680	Profiles
New Jersey						
Island Beach	39.8°/74.1°	98°	0.370	Buoy-44025 WISII-69	8531680	Profiles
Wildwood	39.0°/74.8°	142°	0.200	Buoy-44009 WISII-66	8534720 8536110	Profiles
North Carolina						
Duck	36.2°/75.8°	68°	0.200[b]	FRF gauge	8651370	Profiles
Florida						
St. Augustine	29.9°/81.3°	75°	0.149	WISII-23	8720220	Profiles and aerials
Crescent Beach	29.8°/81.3°	75°	0.139	WISII-23	8720220	Profiles and aerials
Daytona Beach	29.2°/81.1°	60°	0.153	WISII-22	8720220	Profiles and aerials
New Smyrna Beach	29.9°/80.9°	60°	0.138	WISII-22	8720220	Profiles and aerials
California						
Torrey Pines	32.8°/117.3°	270°	0.194	WISSC-002	9410660	Profiles
Washington						
Long Beach	46.5°/124.1°	270°	0.200	Buoy-46209 CDIP-036	9440910	Profiles

[a] Direction is the approximate azimuth of the outward shoreline normal.
[b] A range of values were tested at Duck due to the bimodal nature of the sediment distribution.

In contrast with the West Coast data sets, most of the East Coast data were obtained along mildly sloping, moderate-energy barrier island coastlines. The Florida shoreline data consist of a combination of beach profile data collected by the Florida Department of Environmental Protection Bureau of Beaches and Coastal Systems, and beach width measurements obtained through the analysis of aerial photographs from a variety of sources (Miller, 2001). Based on the availability of Wave Information Study (WIS) hindcasts in the region, the duration of analysis was limited to the period between 1956 and 1995. Shoreline measurements during this 40-year interval were highly irregular due to the combination of data sources used but generally increased in frequency with time. All four Florida sites experience similar wave conditions characterized by a mean annual significant wave height on the order of 1.2 m as measured by National Oceanic and Atmospheric Administration (NOAA) buoy 41009 in 42 m of water. The tidal range increases slightly from south to north along the coastline, with a mean value of 1.4 m reported at Daytona Beach, and a slightly larger value of 1.6 m reported for St. Augustine Beach. Typical threats to this coastline include the sudden erosion due to both hurricanes as well as major winter storms.

The Duck, NC shoreline data were extracted from profiles collected by the U.S. Army Corps of Engineers FRF staff and form only a small subset of the data available along one of the most intensively studied coastlines in the world. Several features make this dataset unique compared to the others. The typical double bar configuration, along with the presence of the research pier and the remarkable stability of the shoreline, makes the site a less than ideal place to apply the model. Nonetheless, the site represents a rigorous test for both the model as well as the shoreline adjustment procedure discussed in the subsequent section. Bathymetric surveys have been conducted along this one-kilometer stretch of coast on a monthly interval (biweekly at four selected sites), since 1981, with more frequent measurements available during the numerous field campaigns conducted at the site. Despite a recognized seasonality in the wave climate in both height and direction, the dominant shoreline fluctuations at Duck occur with periods greater than 1 year (Plant and Holman, 1996; Miller and Dean, 2003). NOAA buoy 44014 recorded a mean annual significant wave height of 1.4 m, in 47.5 m of water, while the tide gauge located on the FRF pier reports a mean tide range of 1.1 m.

Shoreline data at both New Jersey sites were obtained from profiles collected on an annual basis between 1986 and 1994, and on a biannual basis since, by the Richard Stockton College of New Jersey and the New Jersey Department of Environmental Protection. The profiles extend to wading depth and have been collected at more than 100 sites along New Jersey's coastline. Wildwood is the site of the widest beach in New Jersey stretching over 300 m from the boardwalk to the mean high-water line. The Island Beach site is located farther north and is one of the last natural or undeveloped stretches of coastline left in New Jersey. The most significant threats to the New Jersey shoreline are the strong winter storms and northeasters that frequent the region. Typically, offshore wave heights range from 0.9 to 1.6 m throughout the year, with a mean annual significant wave height of 1.2 m measured by NOAA buoy 44025 in 40 m of water. The tide along the New Jersey coast is semidiurnal, with an average range along much of the coast of approximately 1.5 m.

The shoreline at East Hampton has been monitored extensively since at least 1979 by a variety of state agencies, with the current monitoring being performed by the Marine Sciences Research Center of Stony Brook University. Profiles collected on inconsistent intervals over the past 25 years have indicated that over the long term, the East Hampton shoreline is relatively stable. The dominant mode of variability along this stretch of coastline is a strong annual fluctuation, which corresponds to a distinct seasonal pattern in the wave climate. The mean annual significant wave height recorded by NOAA buoy 44025 in 40 m of water is 1.2 m, although waves as large as 9.2 m have been recorded during the winter months. The tidal range at the site is approximately 1.1 m and contains a dominant semidiurnal component.

Local conditions, including both wave and water level information, were obtained from extensive databases of measured and hindcast data, which have been collected and maintained primarily by various branches of the U.S. Federal Government. The primary source of wave data was the extensive network of directional and non-directional buoys maintained by the National Data Buoy Center of the National

Oceanic and Atmospheric Administration (NOAA). Other sources of measured wave data include several wave gauges maintained by the FRF staff at Duck, NC and a series of gauges along the West Coast maintained by Scripps Institution of Oceanography, including one at Grays Harbor, WA. In cases where measured wave data were unavailable, or unsuitable due to the length of the data set, U.S. Army Corps of Engineers Wave Information Study (WIS) hindcasts were utilized. In a few cases, multiple sources of wave data were required to help fill in gaps in the primary record. The source(s) of wave data for each site is/are provided in Table 1. Generally, the measured wave data are available on an hourly basis, while the hindcasts are reported at 3-h intervals.

Historical water levels were obtained on an hourly basis from a database maintained by NOAA and the National Ocean Service (NOS). Unfortunately, at several sites, the nearest gauge contained an incomplete record during the period of interest. In these cases, records from the nearest gauge with a complete data set were used to represent the local water surface elevation. Where necessary, tide factors were calculated and applied to more closely matched magnitude and phase of the local conditions. The source of water level information at each site is given in the second to last column of Table 1 where the number represents the NOAA station identifier.

4.2. Field site evaluation

A shoreline adjustment procedure was applied at Duck, NC and Torrey Pines, CA in an effort to isolate the shoreline changes due to cross-shore processes, from those resulting from changes in sediment volume within the profile and presumably due to gradients in the longshore sediment transport. This adjustment technique has the potential to remove a significant portion of the long-term trend from the data by using physical arguments, which is considered much more accurate than simply removing a linear trend. Unfortunately, the procedure could only be applied at Duck and Torrey Pines where the profile data extend past the approximate depths of closure for each site. The change in sediment volume within a profile between two successive surveys, $\Delta V(t)$, is assumed to result from longshore processes not included in the model. The shoreline adjustment, $\Delta y(t)$, is based upon the assumption of a uniform profile translation and is given by:

$$\Delta y(t) = \frac{\Delta V(t)}{(h^* + B)} \tag{10}$$

where h^* is the approximate depth of closure and B is the berm height. Eq. (10) assumes that the effect of an addition to or removal of sediment volume from the profile does not change the profile form and that this volume change is distributed evenly over the vertical dimension of the active profile, $(h^* + B)$. Based on these assumptions, the result is a uniform cross-shore translation of the profile by a distance $\Delta y(t)$. Fig. 3 illustrates the difference between the adjusted and raw shorelines at Duck. The improved correlation between shoreline changes on opposite sides of the pier is obvious, suggesting that sediment impoundment/starvation due to pier effects is at least partially responsible for some of the nonuniform shoreline behavior near the pier. The same procedure applied at Torrey Pines resulted in relatively small shoreline adjustments, reflecting the relatively minor influence of longshore processes on a short, uninterrupted coastline.

In a strict sense, the applicability of the shoreline adjustment procedure at Duck may be questioned. The bimodal nature of the sediment size distribution at Duck, consisting of coarser sediment in the nearshore region, complicates the analysis. The assumption of profile translation without change of form is dependent on both the distribution and composition of any volume change. This concept would not be valid if the volume changes were associated with sediment sizes different than those initially present or if the volume changes were concentrated at either end of the profile without allowing for adequate equilibration time (which may be in the order of years). The profile would be expected to respond in a nonuniform manner to volume changes resulting from either the removal or addition of sediment consisting of a single grain size. In addition, studies by Larson and Kraus (1994) and Haines et al. (1999) have indicated that the nearshore region at Duck receives episodic "bursts" of sediment from offshore. These bursts of sediment slowly move onshore, with time scales of approximately 1 year. The combination of these two factors suggests that some of the extreme shoreline

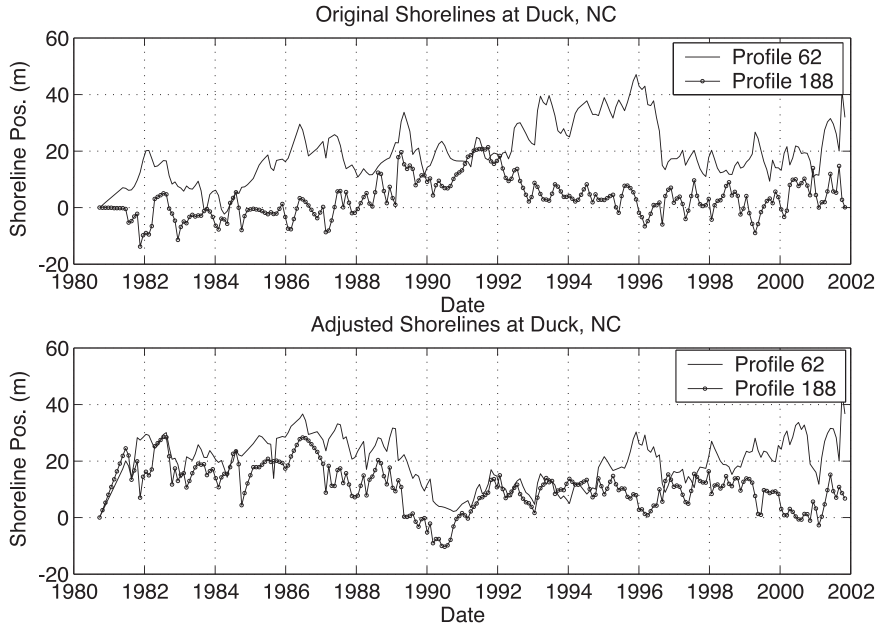

Fig. 3. Improvement in the correlation between shoreline changes north and south of the pier at Duck when volume changes within the profile are accounted for.

adjustments (some in excess of 20 m) are probably unrealistic. With no adequate method to account for the portion of the volume change that actually manifests itself as a shoreline change, the adjusted shorelines are accepted as an improvement over the raw shorelines due to the apparent improvement in longshore uniformity reflected in Fig. 3.

As discussed previously, the model is not designed to resolve small-scale shoreline changes, making the selection of appropriate data sets for the model's evaluation extremely critical. Considering that the spatial resolution of the model is equal to that of the forcing wave and water-level data and can be on the order of kilometers, it is most appropriate to utilize several sets of adjacent shoreline data to evaluate/validate the model. Comparisons between the model hindcasts and historical shoreline positions were performed utilizing longshore averaged shorelines wherever possible. Although this technique should remove most local effects, such as sand waves and beach cusps that the model is not designed to predict, in some cases, remnants of these effects may remain and can mask the more homogenous changes induced by the variations in the forcing conditions. The degree to which the longshore average represents the true mean behavior of the shoreline is a function of a number of variables including the length of shoreline under analysis and the density of the measurements available. Unfortunately, when dealing with sparsely sampled data such as historical shoreline data, these variables are predetermined, giving the researcher few opportunities to improve the statistical reliability of the data.

Plant et al. (1999) present a convenient method for quantifying the longshore uniformity of a shoreline. They isolate the longshore uniform portion of the shoreline variance, s_{lsu}^2, and compare it to the total variance in the system. In our case, the longshore uniform portion of the variance is essentially the temporal variance of the longshore averaged deviations from the time mean shoreline location.

$$y'(x,t) = y(x,t) - y_t(x) \tag{11}$$

$$s_{\mathrm{lsu}}^2 = \frac{1}{\mathrm{nt}}\sum_{j=1}^{\mathrm{nt}}(y'_x\,)t_j))^2 \tag{12}$$

where x and y represent the longshore and cross-shore coordinates respectively and the subscripts t and x refer to temporally and spatially averaged quantities. First, the shoreline data are separated into a time mean component, $y_t(x)$, and a time- and space-dependent deviation from this time mean, $y'(x,t)$. The temporal variance of the alongshore average of these deviations defines the uniform component of the total shoreline variance. Comparing the alongshore uniform portion of the variance defined in Eq. (12) to the total variance provides a useful measure of shoreline homogeneity. For a more complete explanation of the variance analysis, the reader is referred to Plant et al. (1999). The results of the variance analysis are presented in Table 2 and provide a preliminary indication as to how representative the longshore averaged shoreline is expected to be at each site. Obviously, the more data available at a given site, the more credence can be given to these results; however, without the means to supplement or improve the data, the results must be interpreted in the correct context, and that is, that they provide a functional measure of the relative uniformity of a given section of coastline. Most of the sites exhibit a satisfactory degree of uniformity (>50%), providing one indicator of their appropriateness for evaluating the proposed model. The two most significant exceptions are the Harvey Cedars site, which is located within a groin field, and the Duck data, which are centered about the FRF research pier. These results are expected as the structures at both sites are recognized to have significant effects on the adjacent shorelines.

Where possible, more detailed statistical analyses were performed to expand upon, and hopefully confirm, the results of the variance analysis. At Duck, NC and Torrey Pines, CA, the correlations between adja-

Table 2
Site characteristics and results of variance analysis to quantify longshore uniformity

Location	Length of coastline (m)	Number of sites	Longshore uniform portion of total variance (%)
New York			
East Hampton	1500	3	59
New Jersey			
Island Beach	9000	3	61
Harvey Cedars	4000	3	33
Wildwood	3500	2	59
North Carolina			
Duck raw shoreline (N of pier)	250	5	82
Duck raw shoreline (S of pier)	250	5	71
Duck raw shoreline (complete)	1000	20	39
Duck adjusted shoreline (N of pier)	250	5	59
Duck adjusted shoreline (S of pier)	250	5	60
Duck adjusted shoreline (complete)	1000	20	22
Florida			
St. Augustine	2500	3	77
Crescent Beach	3250	2	93
Daytona Beach	3500	3	87
New Smyrna Beach	2750	3	89
California			
Torrey Pines raw shoreline	1000	3	83
Torrey Pines adjusted shoreline	1000	3	83
Washington			
Long Beach	8000	4	82

cent sets of shoreline data were analyzed and generally confirmed the results of the variance analysis. The Torrey Pines shorelines exhibit a high degree of correlation for time lags of 0, 6 and 12 months, confirming the seasonal trends observed by Nordstrom and Inman (1975). Spectral analyses performed on the Torrey Pines data highlight the dominance of the low-frequency oscillations, specifically the annual signal.

Although the Duck data are fairly well correlated, if only profiles north or south of the pier are considered, when the entire shoreline is analyzed, the correlation is extremely poor (profiles within 200 m of the pier are excluded from the analysis). This may seem to contradict the result presented in Fig. 3; however, the good correlation between the shoreline changes at profiles 62 and 188, located at the extreme ends of the site, are not typical of the correlations between shoreline data sets located closer to the pier. An interesting result is that the correlation improves significantly offshore, making the Duck data much more appropriate for modeling the deeper parts of the profile, including the bar, as was done by Plant et al. (1999). Spectral analysis of the data indicates shoreline fluctuations at Duck are dominated by low-frequency oscillations with frequencies less than 2 cycles/year. A more detailed discussion of these results is presented in Miller and Dean (2003).

5. Results

5.1. Summary of results

A summary of the model results is presented in Table 3. At each site, five different forms of the rate parameter were evaluated according to:

- Case 1: k constant, average H_b used to define y_{eq},
- Case 2: k constant, significant H_b used to define y_{eq},
- Case 3: k proportional to Ω, significant H_b used to define y_{eq},
- Case 4: k proportional to H_b^2, significant H_b used to define y_{eq}, and
- Case 5: k proportional to H_b^3, significant H_b used to define y_{eq}.

The average NMSE reported in Table 3 is the average of the errors (as calculated by Eq. (8)) for each of the five cases at a given site. The minimum error is the minimum error at a given site and is associated with the form of the rate parameter in the adjacent column.

Unfortunately, none of the five forms for the rate parameter clearly emerged as the best alternative. The average and range of the rate coefficients associated

Table 3
Data characteristics, model results including the average error at each site, the minimum error and the associated form of the rate parameter, and overall performance as quantified by the Model Performance Index (MPI)

Site	Duration of analysis	Number of surveys	Average NMSE	Minimum NMSE	Form of rate parameter	MPI
New York						
East Hampton	1979–1997	102	0.800	0.759	$k=k_\alpha \Omega$	2
New Jersey						
Island Beach	1986–2002	21	0.877	0.815	$k=k_\alpha H_b^2$	2
Wildwood	1986–2002	23	0.705	0.613	$k=k_\alpha H_b^3$	4
(pre-1996)	1986–1995	11	0.301	0.190	$k=k_\alpha H_b^3$	5
North Carolina						
Duck	1980–2002	199	0.950	0.889	$k=k_\alpha H_b^3$	1
Florida						
St. Augustine	1955–1995	18	0.774	0.709	$k=k_\alpha \Omega$	3
Crescent Beach	1955–1995	16	0.819	0.715	$k=k_\alpha$	2
Daytona Beach	1955–1995	26	0.726	0.670	$k=k_\alpha \Omega$	3
New Smyrna Beach	1955–1995	25	0.688	0.632	$k=k_\alpha H_b^2$	4
California						
Torrey Pines	1972–1974	27	0.846	0.555	$k=k_\alpha$	4
Washington						
Long Beach	1998–2002	18	0.330	0.243	$k=k_\alpha$	5

Table 4
Summary of rate coefficient values for various forms of the rate parameter

Form of rate parameter	Form of Y_{eq} (Significant or Average)	Coefficient units	Average coefficient		Range of coefficients	
			k_a	k_e	k_a	k_e
$k=k_\alpha$	Avg	time^{-1}	$3.89_{E\text{-}04}$	$1.74_{E\text{-}02}$	$5.00_{E\text{-}08}-2.50_{E\text{-}02}$	$2.00_{E\text{-}04}-1.00_{E\text{-}01}$
$k=k_\alpha$	Sig	time^{-1}	$4.09_{E\text{-}04}$	$5.01_{E\text{-}03}$	$3.50_{E\text{-}06}-1.00_{E\text{-}02}$	$7.50_{E\text{-}05}-7.00_{E\text{-}02}$
$k=k_\alpha\Omega$	Sig	time^{-1}	$7.64_{E\text{-}05}$	$2.66_{E\text{-}04}$	$2.00_{E\text{-}06}-2.00_{E\text{-}03}$	$1.00_{E\text{-}05}-1.00_{E\text{-}02}$
$k=k_\alpha H_b^2$	Sig	time^{-1} length^{-2}	$1.83_{E\text{-}04}$	$3.06_{E\text{-}05}$	$2.00_{E\text{-}07}-1.50_{E\text{-}01}$	$1.00_{E\text{-}06}-1.00_{E\text{-}02}$
$k=k_\alpha H_b^3$	Sig	time^{-1} length^{-3}	$6.36_{E\text{-}04}$	$5.17_{E\text{-}06}$	$1.00_{E\text{-}07}-3.50_{E\text{-}02}$	$1.00_{E\text{-}07}-2.50_{E\text{-}03}$

with each form of the rate parameter is presented in Table 4. Generally, the extremal values tended to be obvious outliers and were removed prior to averaging the coefficients. The range illustrates the significant spread in the values of the coefficients, even when local factors such as wave height and period and sediment size are taken into account. It was expected that the variability of the rate coefficients from site to site would decrease as the degree of dependence on local conditions increased; however, the current results are inconclusive. The spread in the coefficients, combined with the fact that no particular form of the rate parameter appears significantly better than any other, indicates that it is not possible at this time to establish the appropriateness of one form of the rate parameter over another. Until it can be established that the values of the rate coefficients remain fairly stable at sites with similar local conditions, sufficient local data are required in order to set these coefficients prior to applying the model (even in a hindcast sense). The scatter in the results perhaps argues for keeping the simplest form of the rate parameter, corresponding to either Case 1 or Case 2, until more appropriate rate parameters are developed.

The sensitivity of the predictions to the rate constant was explored by applying the model at each site utilizing the average value of the rate constant for each form of the rate parameter. As stated previously, the extremal values were removed prior to the averaging, in order to minimize the influence of outliers. The third adjustable parameter was determined by minimizing the NMSE, as the relationship between the equilibrium shoreline position and the actual shoreline position is a function of the new rate constants. Table 5 summarizes the results obtained utilizing the averaged coefficients and indicates that on average, the errors increase by

Table 5
Summary of results obtained using average values of the rate coefficients

Site	NMSE		Percent increase in NMSE (%)
	Local coefficient	Average coefficient	
New York			
East Hampton	0.800	0.940	117
New Jersey			
Island Beach	0.877	1.072	122
Wildwood	0.705	0.742	105
(pre-1996)	0.301	0.520	173
Florida			
St. Augustine	0.774	1.902	246
Crescent Beach	0.819	1.419	173
Daytona Beach	0.726	1.039	143
New Smyrna Beach	0.688	0.873	127
California			
Torrey Pines	0.846	1.322	156
Washington			
Long Beach	0.330	1.953	592

less than a factor of two. As expected, the largest increases are seen at sites where the average coefficients deviate the farthest from the locally determined coefficients. If the form of the shoreline evolution equation is appropriate, the results in Table 5 generally confirm that the rate parameters depend in an, as yet, undetermined manner on local conditions.

The results of the categorical assessment procedure are presented in Table 6. As expected, the sites with the lowest NMSE tend to have the greatest proportion of changes predicted correctly. Not surprisingly, these sites also tend to have more complete, high-quality data sets. The last row of Table 6 gives the average model prediction success rate for each category of observed shoreline change, where the Duck data has been excluded, as the model is clearly not applicable at this site due to the significant longshore variability induced by the pier. Generally, the model is most successful in predicting the erosional events (64.7% versus 56.0% and 18.7% for accretional and stable shorelines, respectively). This is related to the more dramatic, episodic nature of the erosion process both in nature and in the model. Because the erosional shoreline response is nearly instantaneous and the recovery is much more gradual, erosional events (specifically large ones) are rarely miscast as periods of stability. In contrast, the mild nature of the accretion process results in a number of accretional events being falsely categorized as periods of stability, and vice versa. Considering the breadth of the study in terms of the temporal scales and the diversity of the shorelines investigated, the average of total prediction percentage 56.7% is considered acceptable.

5.2. Daytona Beach, FL

In order to clarify the way in which the MPI was applied at each site, an example from Daytona Beach, FL is provided. In Fig. 4, model predictions for each of the five forms of the rate parameter are plotted along with the measured data, serving to illustrate a case where one large deviation from the measured data significantly influences the error and resulting in a fairly large NMSE, despite good overall performance by the model. A purely objective measure of skill such as the NMSE is incapable of differentiating between good predictions such as those in Fig. 4, and predictions that may miss the mark completely but match at certain strategic locations such as the extrema. This illustrates the need for a subjective measure of model skill such as the MPI which takes these subtleties into

Table 6
Results of categorical assessment procedure

Location	Accretion (%)	Erosion (%)	Stable (%)	Total (%)[a]
New York				
East Hampton	30.6	27.0	62.0	38.2
New Jersey				
Island Beach	33.3	57.1	60.0	47.6
Wildwood	45.5	54.5	0.0	47.8
(pre-1996)	60.0	100.0	0.0	70.0
North Carolina				
Duck	1.5	4.8	97.0	34.7
Florida				
St. Augustine	57.1	44.4	0.0	44.4
Crescent Beach	42.9	75.0	0.0	56.3
Daytona Beach	63.6	77.8	16.7	57.7
New Smyrna Beach	60.0	83.3	0.0	64.0
California				
Torrey Pines	66.7	50.0	30.0	51.9
Washington				
Long Beach	100.0	77.8	–	88.9
Average	56.0	64.7	18.7	56.7

[a] Total number of events predicted correctly over the total number of events multiplied by 100, and is not equivalent to the average of the preceding three columns unless the probability of each event occurring is the same, i.e., 0.333.

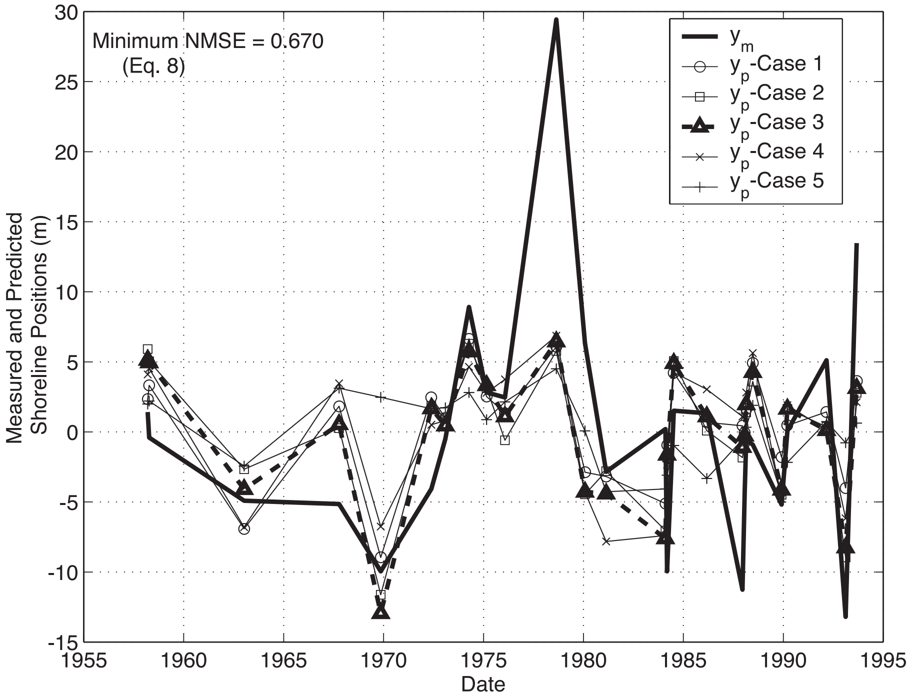

Fig. 4. Comparison of observed and hindcast shorelines at Daytona Beach, FL. The large deviation in 1978 disproportionately influences the overall mean square error.

consideration. The important factors contributing to the final MPI rating of 3 at Daytona Beach are:

- significant longshore uniformity, indicating the potential applicability of the model at the site,
- larger than desired minimum and average NMSE (however, a significant portion can be attributed to a single outlier) and
- adequate forcing and shoreline data for comparison.

The final MPI reflects the balance between the potential for good model predictions at the site and the fairly large errors between the hindcasts and shoreline data, with consideration given to the significant proportion of the error associated with the disagreement between the shoreline data and the model hindcast at a single point.

A more detailed portrayal of the model's behavior is given in Fig. 5, in which a complete time series of model predictions at Daytona Beach is plotted. The model predictions correspond to Case 3 where the rate parameter is assumed to be a function of the fall velocity parameter, specifically, $k(t) = 2 \times 10^{-4}\Omega(t)$ h^{-1} for accretion and $k(t) = 4 \times 10^{-5}\Omega(t)$ h^{-1} for erosion. In this case, the accretion coefficient (2×10^{-4} h^{-1}) is larger than the erosion coefficient (4×10^{-5} h^{-1}); however, $\Omega(t)$ during erosional events exceeds those for accretional events [the same logic applies for $k = f(H_b^2, H_b^3)$]. When the complete rate parameter is considered, $k(t) = k_\alpha\Omega(t)$, the characteristics of the natural system are preserved, and erosion occurs more rapidly than accretion. The dominance of the annual signal, corresponding to annual periodicities in both the wave and water level forcing, is evident. The inset chart illustrates a typical year with both winter storm and hurricane impacts. The typical seasonal trend on Florida beaches consists of fairly rapid erosion in response to energetic hurricane or winter conditions, followed by a more gradual recovery during the milder summer months. The inset plot illustrates this typical behavior, where, for the year in question, the shoreline begins to recover from the previous winter's erosion in approximately mid-February. The recovery period is cut short, however, due to the occurrence of Hurricane Diana in September 1984. In comparison to the gradual shoreline recovery, the storm-induced erosion occurs

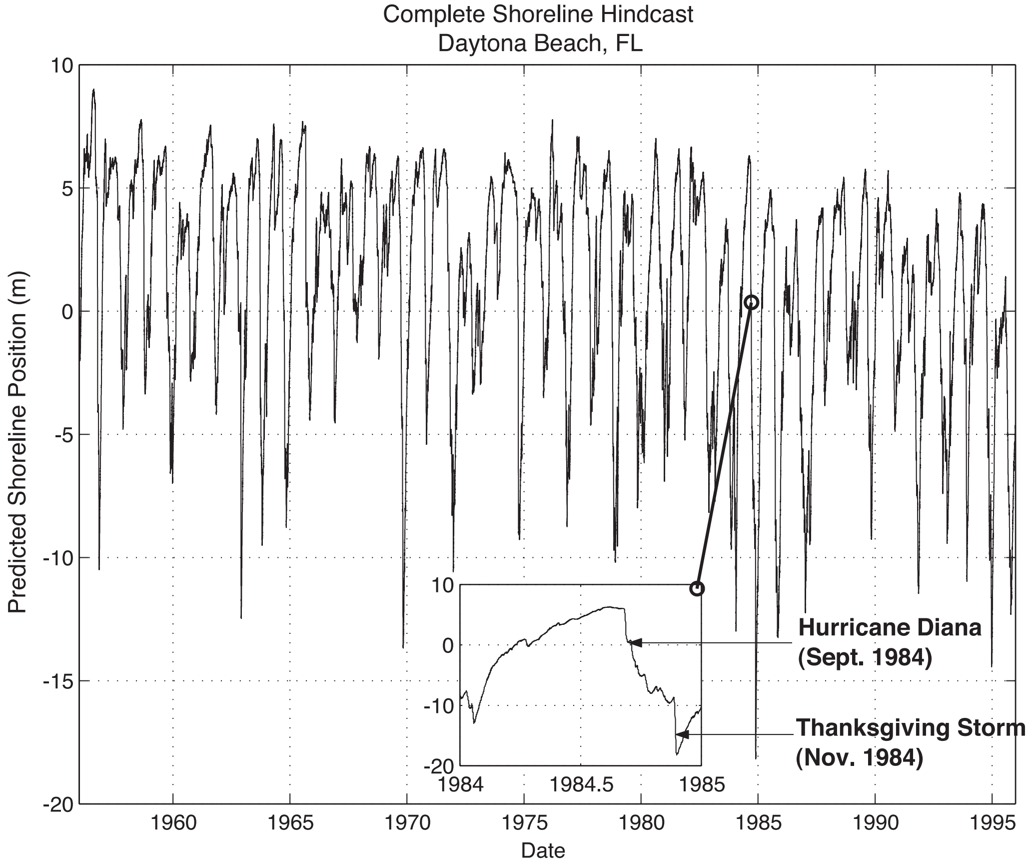

Fig. 5. Complete time series of shoreline hindcasts at Daytona Beach, FL ($k_a(t) = 0.0002\Omega(t)$, $k_e(t) = 0.00004\Omega(t)$).

nearly instantaneously. The "Thanksgiving Storm" of November 1984 exacerbates the situation and erodes the shoreline even further. The model mimics nature in that hurricanes cause a more immediate (although less severe in terms of overall magnitude) erosional response compared to winter storms. The nature of the equilibrium-based model is such that a larger portion of the potential erosion (or accretion) will be reached for conditions persisting over longer periods. In a broad sense, the seasonal oscillations predicted by the model agree reasonably well with the results of DeWall (1977) who observed seasonal shoreline fluctuations on the order of 20 m at Jupiter on the southeast coast of Florida.

5.3. Washington State

A majority of the model results (at 6 of the 10 sites) are characterized by reasonable to excellent MPI's (3–5), as indicated in Table 3. Of the 10 sites at which the model was applied, the Washington State shoreline data are modeled most accurately. Comparisons between model hindcasts and the average observed shoreline positions are presented in Fig. 6. The first observed shoreline is used as an initial condition for the model, and is therefore omitted from the plot and all error calculations. An unfortunate consequence of omitting the initial point from plots such as Fig. 6 can be the illusion of a long-term trend in both the measured and predicted data; however, as discussed in Section 3, all of the datasets have been detrended prior to using them with the model. The various line styles in the figure correspond to each of the five methods for defining the rate parameter mentioned previously, with the solid bold line representing the measured shoreline and the dashed bold line representing the hindcast shoreline with the minimum

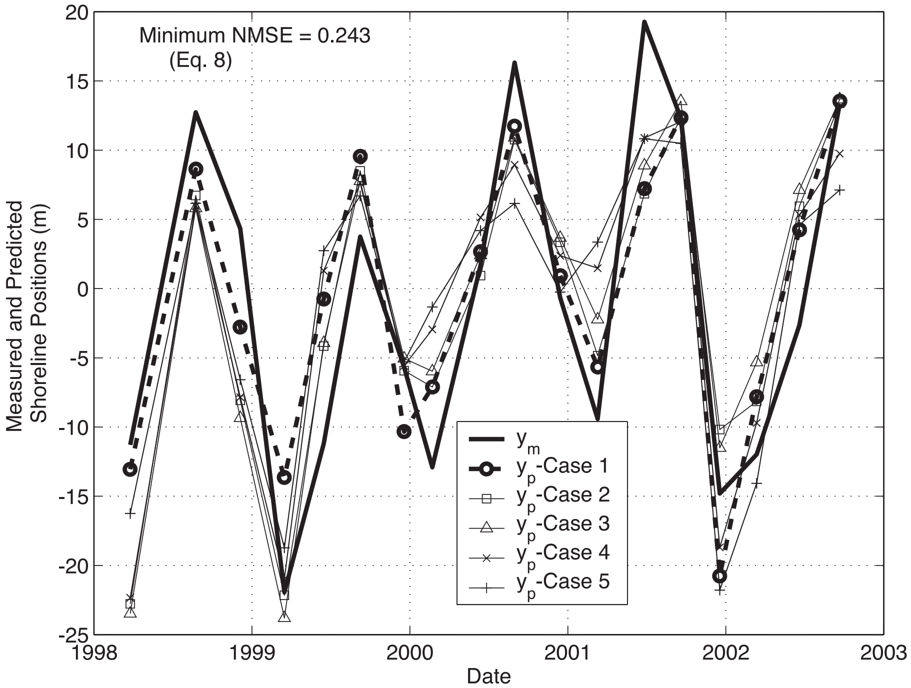

Fig. 6. Comparison of observed and hindcast shorelines at Long Beach, WA.

NMSE. In all plots of this type, the small differences between the various cases, represented by the different line styles, are less important than the general behavior of the model. As shown by the figure, the goodness of fit to the data does not vary significantly for different forms of the rate parameter at this site. In this specific case, the minimum NMSE of 0.243 was obtained with a constant rate parameter and an equilibrium shoreline position based upon average breaking wave heights (Case 1). At the Washington site, the NMSE ranged from 0.243 to 0.401 depending upon the form of the rate parameter used.

Several factors contributed to the success of the model at the Washington site. The high degree of uniformity exhibited by the shoreline over a long segment of coastline was undoubtedly an important factor. Also significant was the quality of the wave and water level information at this site. A NOAA tide gauge was located just to the north of the site, and two directional wave gauges, one just to the south of the site operated by NOAA and one just to the north of the site operated by Scripps, were available. The length and temporal resolution of the Washington data may also have had a significant effect on the favorable results. Results from a number of sites indicate that the model is most successful in predicting the seasonal shoreline changes corresponding to the strong annual signal in the wave and water level data. The relatively short Washington data set containing a dominant annual signal, sampled quarterly, make this data set ideal for evaluating model skill in predicting seasonal and long period changes. A more detailed analysis of the model predictions indicates significant shoreline change is predicted in connection with several large winter storms; however, without more frequent shoreline data to compare the results with, it is impossible to assess the accuracy of the model at this shorter time scale.

5.4. New Smyrna Beach, FL and Wildwood, NJ

The model results at Washington are considered excellent, although not entirely representative of the overall model performance. The results for two

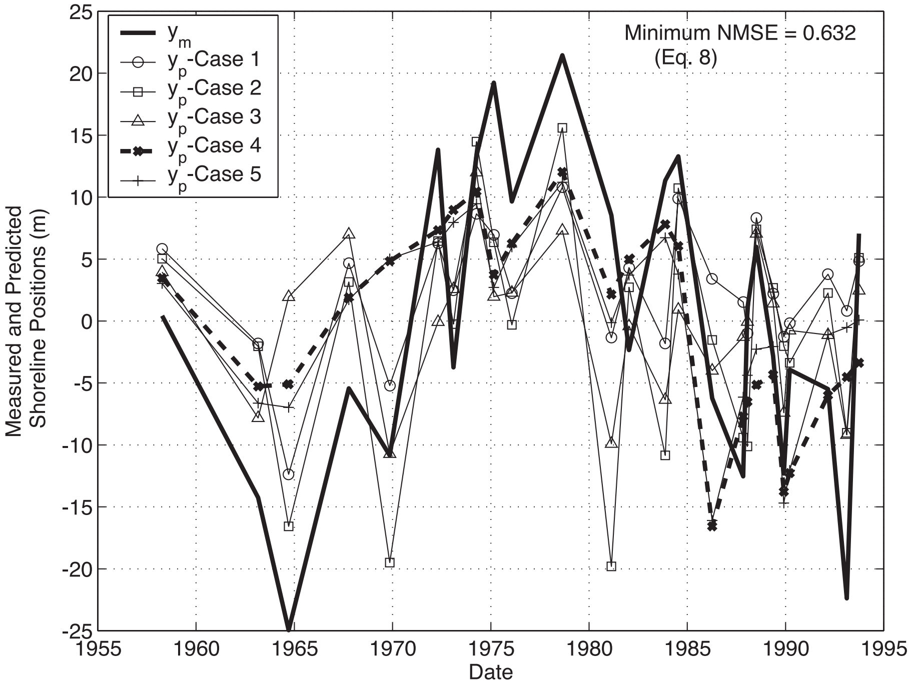

Fig. 7. Comparison of observed and hindcast shorelines at New Smyrna Beach, FL.

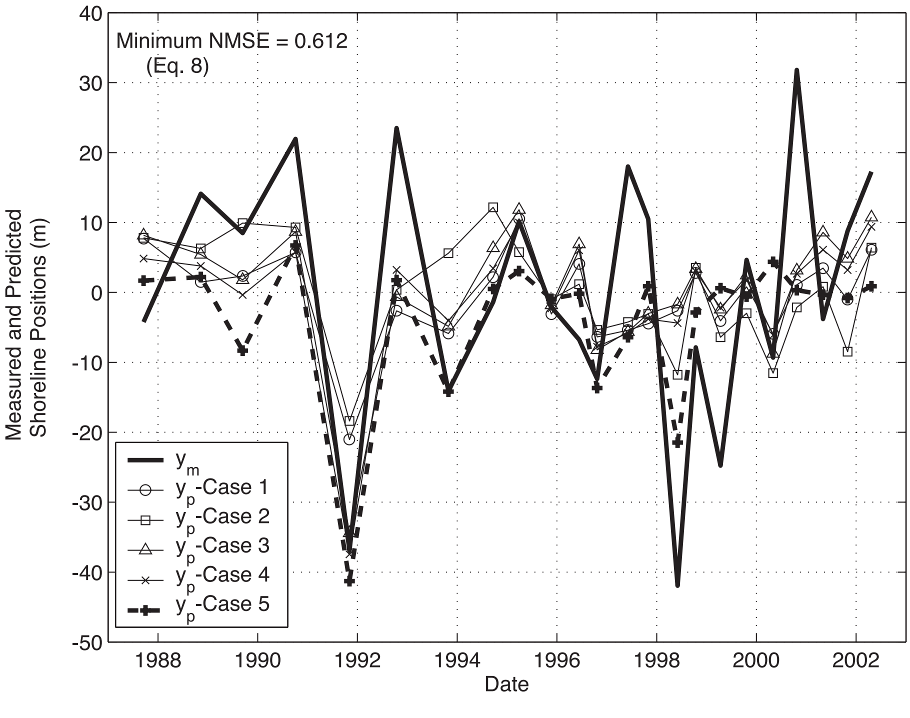

Fig. 8. Comparison of observed and hindcast shorelines at Wildwood, NJ.

additional sites, New Smyrna Beach, FL and Wildwood, NJ, are depicted in Figs. 7 and 8. Both figures illustrate the overall ability of the model to accurately hindcast the observed shoreline changes, despite neither site being considered ideal. The New Smyrna Beach shoreline data were compiled at three adjacent locations over a 40-year period using a combination of measured profile data and aerial photography. Although the shoreline changes at New Smyrna Beach are very uniform (93%), high-quality measured wave and water level data were not locally available. The length of the shoreline data set at New Smyrna Beach precluded utilizing measured wave data for the entire period, and therefore, WIS hindcasts were substituted for measured data. In Florida, added uncertainty is caused by the exclusion of hurricanes and tropical storms in the WIS hindcasts prior to 1976. The length of the shoreline data sets and the location of the sites in Florida also required the use of a remote tide gauge to obtain water levels which were then related to the local conditions. Finally, most of the Florida shoreline position data were obtained via analysis of aerial photographs, incorporating the uncertainties inherent in that procedure, into the model results. Despite many potential sources of error, the model performs well at New Smyrna Beach, with an MPI of 4, based largely upon the NMSE, and the ability of the model to represent most of the shoreline changes. Fig. 7 illustrates the importance of incorporating some subjectivity into the MPI. Although the best results (minimum NMSE) are obtained with the rate parameter as a function of the breaking wave height squared, it is obvious that other versions of the rate parameter actually perform better despite having larger NMSE values. One of the consequences of using the NMSE definition is that, any error minimization procedure may assign a smaller error to a conservative hindcast, which minimizes the number of large deviations, and not necessarily to a more aggressive hindcast that provides a superior overall fit, but contains a few large deviations.

A number of factors at Wildwood also make it a less than ideal site at which to apply the model. The Wildwood shoreline data were collected at two adjacent sites over a 16-year period, and consisted of annual surveys between 1986 and 1994 and semiannual surveys thereafter. Although the variance analysis technique at Wildwood indicates that only 59% of the shoreline variance is longshore uniform, that number is somewhat misleading. Examining the individual shoreline time series, it becomes obvious that a significant portion of the nonuniformity occurs in association with a single survey. Immediately following the "Perfect Storm" or "Halloween Storm" in October 1991, one of the profiles eroded significantly as would be expected, while the other accreted. It is hypothesized that while during a normal event, both shorelines are sufficiently far from a nearby inlet; during an extremely powerful storm such as the Perfect Storm, the shoreline in closest proximity to the inlet is affected, in this case, accreting as the updrift jetty blocks the predominant southerly longshore sediment transport. Although both wave gauges (nondirectional) and tide stations were located nearby, the nondirectional wave gauge proved extremely unreliable, containing significant gaps in the historical wave data. In order to fill in the missing wave data, WIS hindcasts were related to buoy measurements during periods where both were available; and using a linear least squares regression technique, the missing data were replaced by scaled WIS hindcasts. Initially, wind direction (accounting for the 180°-phase difference) was used as a proxy for wave angle; however, this proved inadequate as a number of major storms were missed due to prevailing offshore winds, resulting in waves which were assumed to propagate offshore, and thus, not impact the shoreline. More appropriate results were obtained by making the assumption that all waves approached from the median wave direction, as calculated from the WIS data summaries provided by the U.S. Army Corps of Engineers. Once the missing wave data were accounted for, the results improved substantially (MPI = 4), with the average NMSE reducing to 0.705. After examining Fig. 8 more closely, it became obvious that the model predictions began to deviate from the measured data most significantly after 1996. The interpretation is that the WIS hindcasts were only available through 1995, leaving considerable gaps in the wave record between 1996 and 2002. If the model is applied only over the period for which the wave record is complete, the results improve dramatically as shown in Fig. 9.

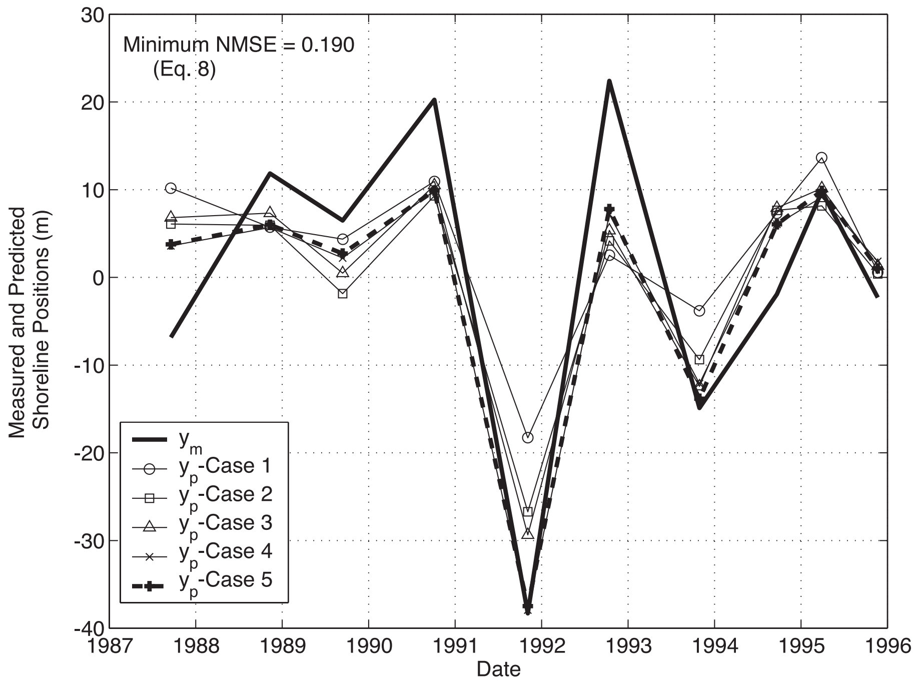

Fig. 9. Comparison of observed and hindcast shorelines at Wildwood, NJ. Only years with complete wave data (1987–1995) are included.

The NMSE associated with the shortened data set ranges from 0.190 to 0.493. These results are interpreted cautiously, however, because although excluding the post-1995 data appears justified given the significant gaps in the forcing data, the improvement of the results due to other factors, including simply shortening the prediction window, cannot be ruled out.

5.5. Torrey Pines, CA

In addition to the previously described analyses performed at each of the other sites, the quality and density of the surveys at Torrey Pines, CA allow for some additional, traditional statistical techniques to be employed. Interpolating the shoreline data to constant 15-day intervals allows correlation analyses as well as spectral analyses to be performed. Figs. 10 and 11 present the results of a lagged cross-correlation analysis. Shoreline time series are plotted in the upper panels of both figures, with the three measured shorelines plotted in Fig. 10a and the averaged measured shoreline and the model hindcast plotted in Fig. 11a. The lower panels illustrate the results of a lagged correlation analysis, where it is seen that the correlation between the model hindcast and the average measured shoreline (Fig. 11b) is very similar to the correlation between individual measured shorelines (Fig. 10b). Unfortunately, the normalized correlation only measures the linear association between the two variables and gives no information regarding their relative magnitudes. From Figs. 10(a) and 11(a), it is obvious that although the model successfully predicts the dominant annual trend, it significantly underpredicts the amplitude of the fluctuations. A portion of this underprediction is again attributed to the preference given to conservative predictions by the NMSE. Spectral analyses performed on both the observed and hindcast shorelines indicate very similar behavior in the frequency domain, although the amplitudes of the various frequency components in the hindcast spectrum are significantly smaller. A comparison of the resulting spectra normalized by the total variance, as presented in Fig. 12, illustrates the qualitative agreement between the two spectra. The

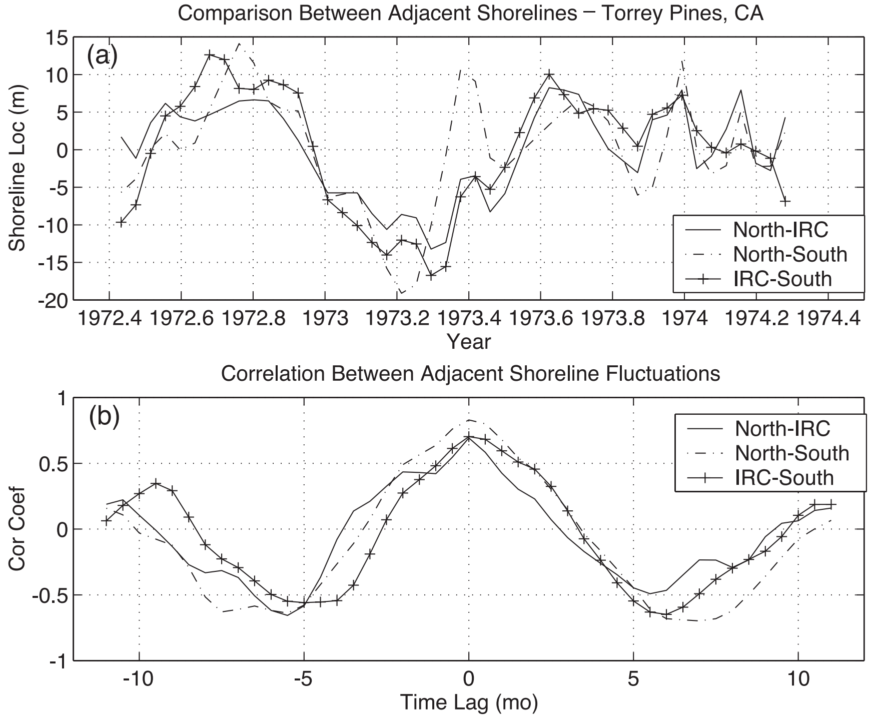

Fig. 10. (a–b) Correlation coefficient between measured shoreline time series at three locations at Torrey Pines, CA.

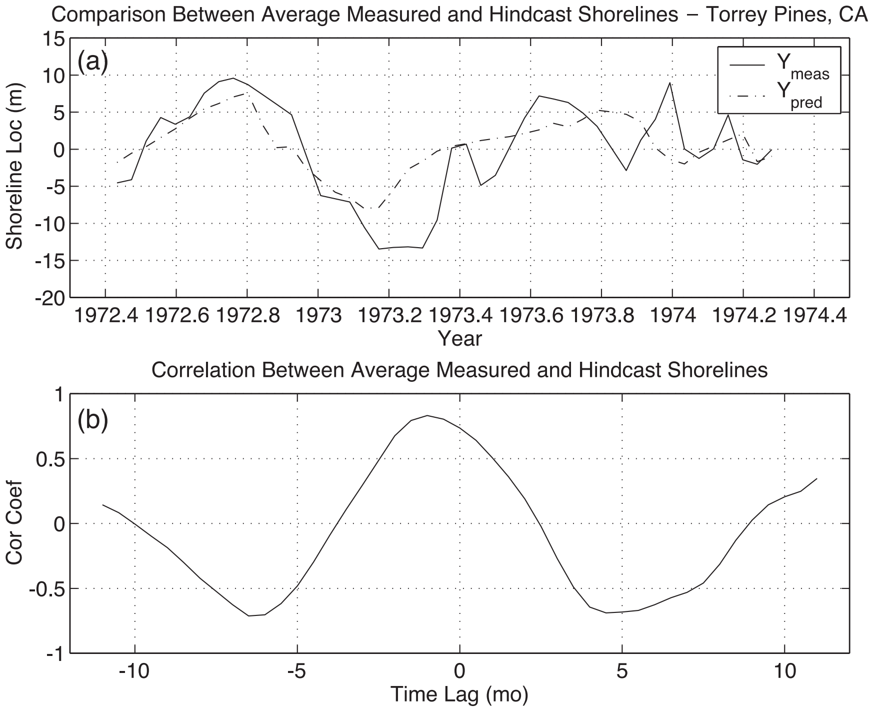

Fig. 11. (a–b) Correlation coefficient between measured and hindcast shoreline time series at Torrey Pines, CA.

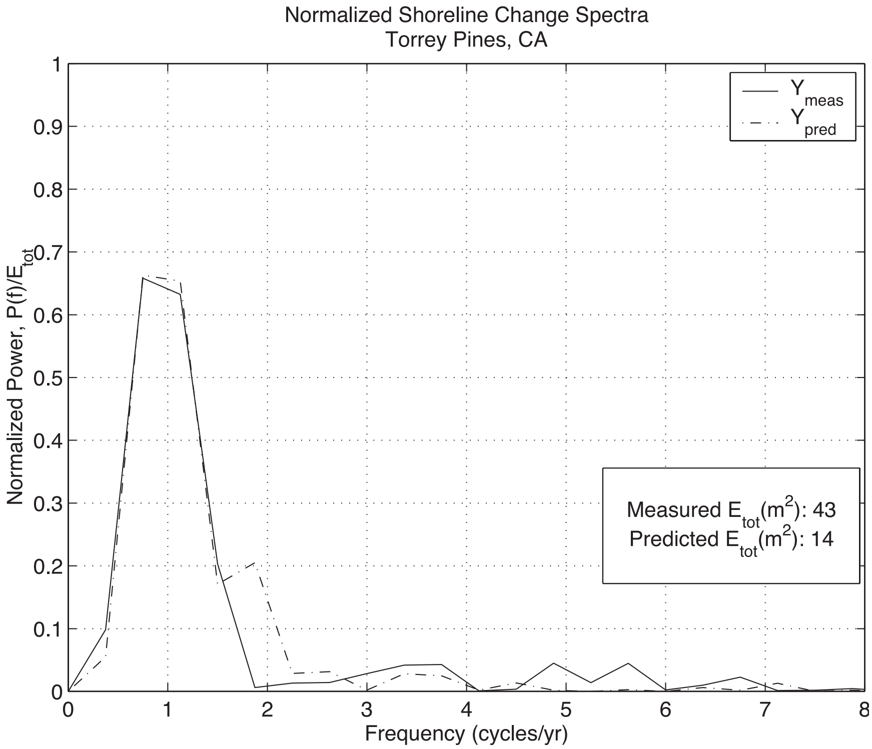

Fig. 12. Normalized results of spectral analyses performed on measured and hindcast shoreline time series (shown in Fig. 11a) at Torrey Pines, CA.

difference in the magnitude of the various frequency components is indicated by the difference in the total energy or variance (E_{tot}) for the two spectra, as tabulated in Fig. 12.

6. Conclusions

A simple new shoreline change model has been proposed, calibrated and evaluated at a number of sites. The model is based upon previous numerical and experimental results that indicate a shoreline approaches an equilibrium state with a form that is approximately exponential with time. The equilibrium or linear relaxation equation suggested by these observations has proved useful in other areas of coastal engineering, and is utilized successfully here, to model shoreline changes associated with cross-shore processes. By solving the equation numerically, realistic, complex variations in the equilibrium shoreline position can be used to drive the model, as shoreline changes are forced by time-dependent wave and water level variations. The model is only intended to be applicable for the prediction of large-scale shoreline changes due to cross-shore processes, on relatively straight uninterrupted shorelines.

The model has been calibrated and evaluated with historical shoreline data sets at 10 different sites in 6 states, covering a wide geographic region and representing a diverse range of beach, wave and tide conditions. The results are promising, with the best results obtained at the sites with the best data. This is considered extremely encouraging and stresses the need to continue collecting high-quality field data at as many sites as possible, encompassing a variety of beach conditions. Presently, the model appears to be most successful at predicting medium-scale temporal shoreline changes such as seasonal fluctuations. Unfortunately, the model has not exhibited good skill in predicting changes over shorter time scales, although evaluation of the model at this scale is hindered by a lack of data. As expected, the results indicate that shorelines exhibiting a high degree of longshore uniformity are modeled more accurately. Overall, the model is successful in predicting the correct direction of shoreline change; however, it tends to be slightly conservative and generally underpredicts the magnitude of change. The model is most successful at predicting large erosional events and is least successful in differentiating between periods of mild accretion and stability, often miscasting one as the other.

There are several possibilities for significant model improvement. More high-quality data sets consisting of shoreline measurements and local wave and water level information would be invaluable in developing a more complete assessment of the model capabilities. Better shoreline position data would allow for a more thorough analysis of the proposed model including its performance over shorter time scales, as well as a more exhaustive examination of potential forms for the rate parameter.

The proposed model is not considered a replacement for the many existing process-based profile/shoreline change models but as an alternative. The proposed model provides reasonably accurate results at minimal computational cost and is appropriate for a variety of different users. Some of the potential uses of a model of this type include long-term shoreline predictions utilizing Monte-Carlo techniques, as a real time erosion predictor or as the cross-shore component of a combined one-line/profile model. The many uses for a model of this type, combined with some of the promising results, indicate further evaluation and improvement on simple models of this type is warranted. Eventually, detailed three-dimensional process-based models will undoubtedly result in the most accurate shoreline predictions; however, in the interim, simpler more efficient models can be quite useful in many applications.

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