A methodology is developed in which a simple deterministic shoreline change model is applied in a probabilistic manner as one component of a quantitative coastal change hazards assessment. The main drivers of decadal-scale shoreline change, wave climate and sediment supply, are varied within a range of realistic scenarios to develop over 200 shoreline change model simulations. Through numerous SWAN wave simulations, a lookup table is developed to transform deep water wave conditions to the relatively shallow water offshore boundary of the shoreline change model. By applying the shoreline change model in a Monte Carlo sense, predicted probability density functions for shoreline position can be calculated at any location in the model domain. Approaches for the use of these probabilistic shoreline change modeling results by coastal managers to aid decision making are discussed.

INTRODUCTION
Coastal managers, policy makers, and property owners often desire predictions of future coastal change. Since the forcing conditions that govern future coastal change can only be forecast in a statistical sense, predicting coastal change in a probabilistic manner is more meaningful than predicting a single deterministic outcome. Most informed managers and the public now realize that a range of possible future states (shoreline positions) of the coast may constitute a more accurate system understanding than just a single predicted “line in the sand.” We have been working toward developing a predictive capability for decadal-scale shoreline changes within the Columbia River littoral cell (CRLC, Figure 1), a high-energy dissipative coastline in the U.S. Pacific Northwest (Buijsman et al., 2000; Kaminsky et al., 2001, Ruggiero et al., in press). As for many coasts, decadal-scale shoreline evolution along the CRLC is highly dependent on both sediment supply and wave climate variability. In particular, accurate estimates of Columbia River sediment supply and sediment feeding from the lower shoreface (Kaminsky et al., 2003) are critical components for balancing the sediment budget and are therefore essential for making shoreline change hindcasts and forecasts. Shoreline change is also highly sensitive to directional changes in the incident waves, and therefore sensitive to the occurrence of interannual climatic fluctuations such as major El Niño events (Ruggiero et al., 2005). Fortunately, because net alongshore gradients in sediment transport

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1 Department of Geosciences, Oregon State University, 104 Wilkinson Hall, Corvallis, OR, 97333, USA
2 Coastal and Marine Geology Program, U.S. Geological Survey, 384 Woods Hole Road, Woods Hole, MA, 02543, USA
3 Coastal and Marine Geology Program, U.S. Geological Survey, 400 Natural Bridges Drive, Santa Cruz, CA, 95060, USA
dominate decadal-scale coastal change along portions of this coast (Long Beach Peninsula, Figure 1), shoreline change hindcasts using simple deterministic one-line shoreline change models have demonstrated significant skill (Ruggiero et al., in press, Figure 2). In this paper we develop a methodology for applying a simple (heavily parameterized) shoreline change model in a probabilistic manner as one component of quantitative coastal change hazards assessments. We focus our efforts along the Long Beach Peninsula (Figure 1) due to both the large shoreline change signals and the clear importance of net gradients in longshore sediment transport rates in causing these changes. Our probabilistic approach reveals how uncertainty in input conditions (wave forcing and sediment supply) is transferred to a range of predicted shoreline positions (e.g., Vrijling and Meijer, 1992). To facilitate the operational use of this probabilistic modeling approach knowledge and tools are being developed for synthesizing realistic input time series, for the efficient statistical analysis of the model output, and for the determination of forecast model skill.

**METHODOLOGY**

**Shoreline Change Model**

Strong gradients in longshore sediment transport rates and clear shoreline change trends (Buijsman et al., 2001) suggest that the beaches of the Long Beach Peninsula are suitable for one-line shoreline change modeling (Hanson et
One-line theory, first developed by Pelnard-Considere (1956), is based on the assumption that the cross-shore profile shape remains unchanged as the shoreline position varies. Therefore, only one contour (line) is necessary to describe the evolution of the beach planform as individual profiles are assumed to move horizontally over the entire active profile height as a result of erosion or accretion. Here we employ the quasi-2D numerical one-line shoreline change model UNIBEST-CL (WL|Delft Hydraulics, 1994), an acronym for Uniform Beach Sediment Transport, to both hindcast and forecast shoreline changes. Like other one-line models, UNIBEST makes many simplifying assumptions leading to severe model limitations, e.g. not all of the processes that move sediments are represented. In the approach developed here, we use the shoreline change model primarily as a tool for understanding the drivers of large-scale coastal evolution and the effect of the variability of these drivers.

UNIBEST solves the one-line shoreline change continuity equation with four options for boundary conditions: the shoreline position remains constant, the shoreline angle remains constant, the sediment transport, $Q$, at the boundaries remains a user-defined constant, or the sediment transport at the boundaries is a user-defined function of time. UNIBEST can be applied to beaches of arbitrary cross-shore profiles (Figure 1B), with straight and parallel depth contours which are modified by obliquely incident random wave fields. UNIBEST transforms incident waves from the offshore extent of individual cross-shore profiles (in our case the five individual profiles shown in Figure 1B extend to 15 m

Figure 2. Measured and modeled decadal-scale (1995-2004) shoreline change along the Long Beach Peninsula, WA.
MLLW) to the shoreline, accounting for refraction, shoaling, and dissipation by wave breaking and bottom friction using a random wave propagation and decay model (Battjes and Stive, 1984). A prescribed sequence of approaching wave heights, periods, and directions (typically derived from a schematization of the wave climate rather than any particular observed time series) is used to calculate the cross-shore distribution of wave height, wave setup, and longshore currents via the momentum equation, accounting for bottom friction, gradients in the radiation stress, and tidal currents if appropriate (not used here). Along each profile, the cross-shore distribution of longshore sediment transport is typically calculated using one of several total load sediment transport formulae such as Bijker (1971) or Van Rijn (1989). Alongshore gradients in the cross-shore integrated longshore transport dictate shoreline evolution patterns of erosion or accretion.

The two primary drivers (and the main inputs to the shoreline change model) of decadal scale shoreline changes along the Long Beach Peninsula are the wave climate and the sediment supply. Detailed analyses of topographic and bathymetric changes over the last century have led to a quantitative sediment budget for the region (Buijsman et al., 2003) that has been used to develop sediment supply boundary conditions for shoreline change modeling. Relatively long time series of offshore wave conditions (> decade) has also allowed us to quantitatively characterize the trends and variability in the wave climate. However, since future forcing conditions (e.g., wave climate and sediment supply) can be predicted only in a statistical sense, our approach for generating decadal scale shoreline forecasts involves multiple runs of the shoreline change model in a Monte-Carlo setting that varies both the environmental forcing (Dong and Chen, 1999) and the sediment supply boundary conditions. Figure 3 illustrates our approach consisting of the combination of M sediment supply scenarios with N wave climate scenarios to develop M*N shoreline change model scenarios. In the following paragraphs we discuss the development of the various scenarios and our approach for transforming the measured deep water wave climate to the offshore boundary of the shoreline change model (15 m).

Wave Climate Scenarios

Wave data for this study are derived from the 3-meter discus buoy located offshore of the Columbia River ebb-tidal delta in approximately 128 m of water (National Data Buoy Center, Buoy 46029, 46°07' N 124°30' W, Figure 1). The wave record at the Columbia River buoy has wave height and period data since 1984 and directional data since 1996. The wave record derived from this buoy reveals a CRLC wave climate characterized by summer waves with a monthly mean significant wave height \( H_s \) between 1 and 2 m, a peak period \( T_p \) between 8 and 10 seconds, and a direction \( \theta \) from west to northwest. Winter waves have monthly mean \( H_s \) between 2 and 4 m, a mean \( T_p \) between 10 and 14
seconds, and mean direction from the west to southwest. Winter storms in the region are intense, with significant wave heights exceeding 10 m and waves approaching the coast from steep southerly angles (Ruggiero et al., 2005). Major El Niño events occur in the region approximately once per decade (Komar, 1986, Allan and Komar, 2002) and are characterized by an increased frequency of extreme waves from the south-southwest and higher than normal sea levels (Komar, 1986; Komar et al., 2000). El Niños have a well documented effect on U.S. Pacific Northwest shorelines; typically shoreline retreat occurs at the southern end of littoral compartments and progradation occurs to the north (Peterson et al., 1990; Kaminsky et al., 1998; Ruggiero et al., 2005).

The probability density functions for wave height, period, and direction from the Columbia River NDBC buoy are shown in Figure 4. Since the shoreline change model has an offshore boundary in relatively shallow water (15 m MLLW), we are faced with transforming these typically deep water waves to the appropriate depth contour. It is obviously impractical to perform this operation on each wave in the ten-year time series so to keep the number of computations manageable we discretize the wave climate into bins of approximately equal probability of occurrence (Figure 4). For this study we develop 18 directional bins (ranging from a width of 3 degrees to a width of 40 degrees), 15 wave height bins (ranging from a width of 0.25 m to a width of 3 m), and 8 wave period bins (ranging from a width of 2s to 7 s). Of the potential 2160 possible combinations of wave height, period, and direction using this discretization, only 1121 of the combinations actually occurred in the measured ten-year time
series. Here we choose to transform only these 1121 wave cases (using the bin mid point for the particular wave parameter) from (approximately) deep water to the 15 m contour to develop a lookup table between offshore wave characteristics and nearshore wave characteristics.

The wave transformations were performed with the wave prediction model SWAN (Simulating Waves Nearshore) version 40.41, a third generation wave model developed at the Technical University of Delft in the Netherlands (Booij et al. 1999; Ris et al. 1999). The model solves the spectral action balance equation using finite differences for a spectral or parametric input (as in our case) specified along the boundaries. The model grid is curvilinear to allow for increased spacing in the area of interest (Long Beach Peninsula). The cross-shore grid spacing varies from about 900 m offshore to 150 m in shallow water while the alongshore grid spacing varies from 1500 m at the north and south boundaries (>50 miles north and south of the extent of the CRLC, Figure 1) to 250 m offshore of Long Beach. The SWAN runs were executed in stationary mode and all model settings varying from default values are discussed below.

The north, south and west boundaries of the model (Figure 5) were specified using grid coordinates and forced using a parameterized JONSWAP spectrum (gamma equal to 3.3) with a directional spread equal to approximately 17 degrees. To ensure that the wave directional spread is sufficiently resolved by the model, we specified 72 directional bins giving a 5 degree directional resolution. Our frequency bins ranged from 0.04 Hz to 0.50 Hz with 48
frequency bins giving a $\Delta f$ of 0.11$/f$, which is variable as the distribution of the frequency bins is logarithmic. Wind was not included in the SWAN simulations (although sensitivity runs including wind were performed with only minor impact on results), therefore no white-capping, energy growth due to wind, or quadruplet wave-wave interactions occur in the simulations. We use the Madsen frictional dissipation option from previous model calibration exercises (Palmsten, personal communication). The model was verified by successfully comparing model output for several wave cases to measured conditions at the Grays Harbor CDIP wave buoy in approximately 43 m of water (Figure 1).

To provide the appropriate input into UNIBEST, we extract the SWAN-modeled significant wave height, mean period, and mean direction along the 15 m contour and then average over several kilometers along the 15 m contour, centered on the five input profile locations of UNIBEST (Figure 5). For each of our 1121 wave cases a simple lookup table is developed that allows for the transformation of wave characteristics from deep water conditions to the 15 m contour at each of the profile locations (Figure 6). This gives us the ability to select any wave condition from the measured ten-year offshore wave time series and use the lookup table to transform this wave condition to the nearshore. For our shoreline change hindcasts, we therefore construct five nearshore time series, each spanning 10 years. From these transformed and alongshore varying wave time series five wave climates are developed consisting of approximately
100 wave conditions, with the appropriate probability of occurrence, for input into UNIBEST. For shoreline forecasts we simply modify the offshore ten-year time series, based on a range of realistic future climate scenarios, and apply this same methodology to develop input into the shoreline change model.

Figure 6. Lookup table between offshore wave conditions (darker line) and onshore wave conditions at each of the five profiles developed by 1121 SWAN simulations.

Buijsman et al. (2000) and Ruggiero et al. (in press) demonstrated the sensitivity of shoreline hindcasts and forecasts to directional changes in the wave climate and to the observed increase in the East Pacific wave climate (Allan and Komar, 2006) over the last several decades. The goal of the present effort is to apply the model in a fully probabilistic sense and to examine the impact of wave climate variability on decadal-scale shoreline change predictions. Wave climate scenarios are developed by modifying the ten-year deep water wave time series by randomly varying the mean wave height, period, and direction of the measured time series. The wave height is varied between ± 0.5 m of the long-term mean, the wave period is varied between ± 2 s of the mean, and the direction is varied between ± 3 degrees. While these conditions certainly represent a broad range of future wave climate variability, they are relatively realistic in that any combination of an increase or decrease in the number of El Niños over the next few decades with the continuation or reversal in the decadal wave height trend could lead to the end members in the range of scenarios being realized. For simplicity, the modified mean parameters of the modified ten-year time series are constants rather than time varying quantities. This more realistic
Sediment Budget Scenarios
Kaminsky et al. (2001) illustrated how trends in bathymetric change data can be used to develop future sediment budget scenarios for shoreline forecasts. Extrapolation of the accumulation and erosion trends of the Columbia River outer and inner ebb-tidal delta/inlet respectively, resulted in a reduction of the sediment flux feeding the Long Beach subcell after 1995 by approximately a factor of two from the historical (1955-1995) rate. Ruggiero et al. (in press) used this process to develop the 9-year shoreline hindcast shown in Figure 2 in which a sediment supply (from the south) into the UNIBEST model domain was 1.4 Million cubic meters (Mm$^3$) of sand per year. To examine the influence of a varying sediment supply on decadal-scale shoreline forecasts we develop three sediment supply scenarios. First is a do-nothing scenario in which the 1.4 Mm$^3$/yr consistently enters the system for the next few decades. Secondly we examine a beneficial use of dredged material scenario in which an addition 0.4 Mm$^3$/yr of sand (approximately a 30% increase) is made available to the system through anthropogenic actions. Finally we examine a sediment supply reduction scenario in which only 1.0 Mm$^3$/yr of sand enters the system from the south. Each of these scenarios is quite realistic in light of current sediment management practices at the Mouth of the Columbia River. In all cases the model domain loses 0.4 Mm$^3$/yr of sand out of the northern boundary throughout the simulation. In addition, for each scenario the application of a cross-shore feeding rate (from the lower shoreface) of 0.4 Mm$^3$/yr (~11.4 m$^3$/yr m$^{-1}$) along the model domain is necessary to balance the sediment budget (Buijsman et al., 2003) and is applied uniformly in the model as a source term every kilometer in the alongshore (see Ruggiero et al., in press for details). Therefore, for all shoreline change simulations Long Beach experiences net accumulation ranging from 1.0 to 1.8 Mm$^3$ of sand per year. The distribution of this material by the various wave climate scenarios governs where zones of shoreline retreat and progradation occur.

RESULTS
The effect of combining a realistic range of sediment supply scenarios (each currently being considered by decision makers who manage dredging and disposal of sand at the Mouth of the Columbia River) with various wave climates for developing a decadal-scale forecast along the Long Beach Peninsula is illustrated in Figure 7. Approximately 70 wave climates are used in combination with the three sediment supply scenarios for a total of over 210 shoreline change model simulations. Taken together the model forecasts give a probabilistic sense of the expected range of future shoreline conditions along the Long Beach Peninsula for these scenarios.
The range of forecasted shoreline change is quite broad, varying from over 600 m in the southern part of Long Beach to approximately 400 m in the north. These large ranges illustrate the sensitivity of the edges of the model to variations in boundary conditions. The range of future shoreline change is much narrower in the middle of the model domain, typically around 100 m. The mean shoreline response of the 70 simulations for each of the three sediment supply scenarios is highlighted in Figure 7. The results suggest that for only a 30% variation from our do-nothing sediment supply scenario the shoreline change forecast varies by ± ~150 m. It is also evident that for these 25-year forecasts the variations in sediment supply only affect the southern half of the model domain.

The results near both alongshore boundaries have the highest standard deviation (Figure 8) and therefore we place our smallest confidence in the magnitudes of predicted coastal change at the boundaries. The approximately 100 m of progradation near kilometer 130 is consistently predicted by virtually every model run (smallest standard deviation) and therefore the confidence in this result is high. Our approach of applying the deterministic model in a probabilistic manner also permits the generation of shoreline change prediction probability distribution functions at specific alongshore locations, as shown by the examples in Figure 8. For the southern most example (km 116) the standard deviation is quite high so again our confidence in the magnitude of the predicted shoreline change is relatively low. However, Figure 8 indicates that 79% of the model simulations indicate that erosion will occur at this location in the next 25
years. The example shoreline prediction PDF at km 130 reveals that 100% of the model simulations show shoreline progradation by 2020. This result is very consistent with our fundamental conceptual model of this coastal system. The northernmost example in Figure 8 suggests that only 10% of our model simulations indicate shoreline erosion at km 145.

![Figure 8. a) Mean and standard deviation of shoreline forecasts. b) Shoreline prediction probability density functions at three alongshore locations.](image)

**DISCUSSION AND CONCLUSIONS**

The future wave climate and sediment supply to coastal systems are not deterministically predictable. Therefore, deterministic shoreline change predictions alone have little value for coastal decision makers. However, by applying a simple deterministic shoreline change model in a probabilistic manner, the influence of variability in environmental forcing and sediment supply boundary conditions can be quantified. For example, a coastal decision maker can have relatively high confidence in the prediction that shoreline erosion will occur in southern Long Beach over the next 25 years, even though the magnitude of the erosion is not precisely known, and plan accordingly. However, only a very conservative coastal decision maker would use the 10% probability of erosion in northern Long Beach to influence land use planning at this location. Although not shown here, coastal managers can also use the temporal evolution of the predicted shoreline probability distribution functions to establish adaptive management plans for their communities.

Along the Long Beach Peninsula in southwest Washington, shoreline response is significantly sensitive to directional changes in the wave climate and therefore
sensitive to the frequency and intensity of future El Niño events. While it is uncertain whether storm intensities and wave heights will continue to increase in the East Pacific in coming decades, shoreline position forecasts are shown to be significantly sensitive to the range of potential variability. Model results also suggest that human manipulation of the sediment budget can affect future shoreline positions on the same order of magnitude as variations in the future wave climate.

Probabilistic simulations of short-term phenomena (extreme storm erosion and flooding) are being treated with other simple models. In future work these results will be superimposed on the shoreline change prediction probability distributions to develop quantitative multi-scale coastal hazards assessments.

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Shoreline forecast